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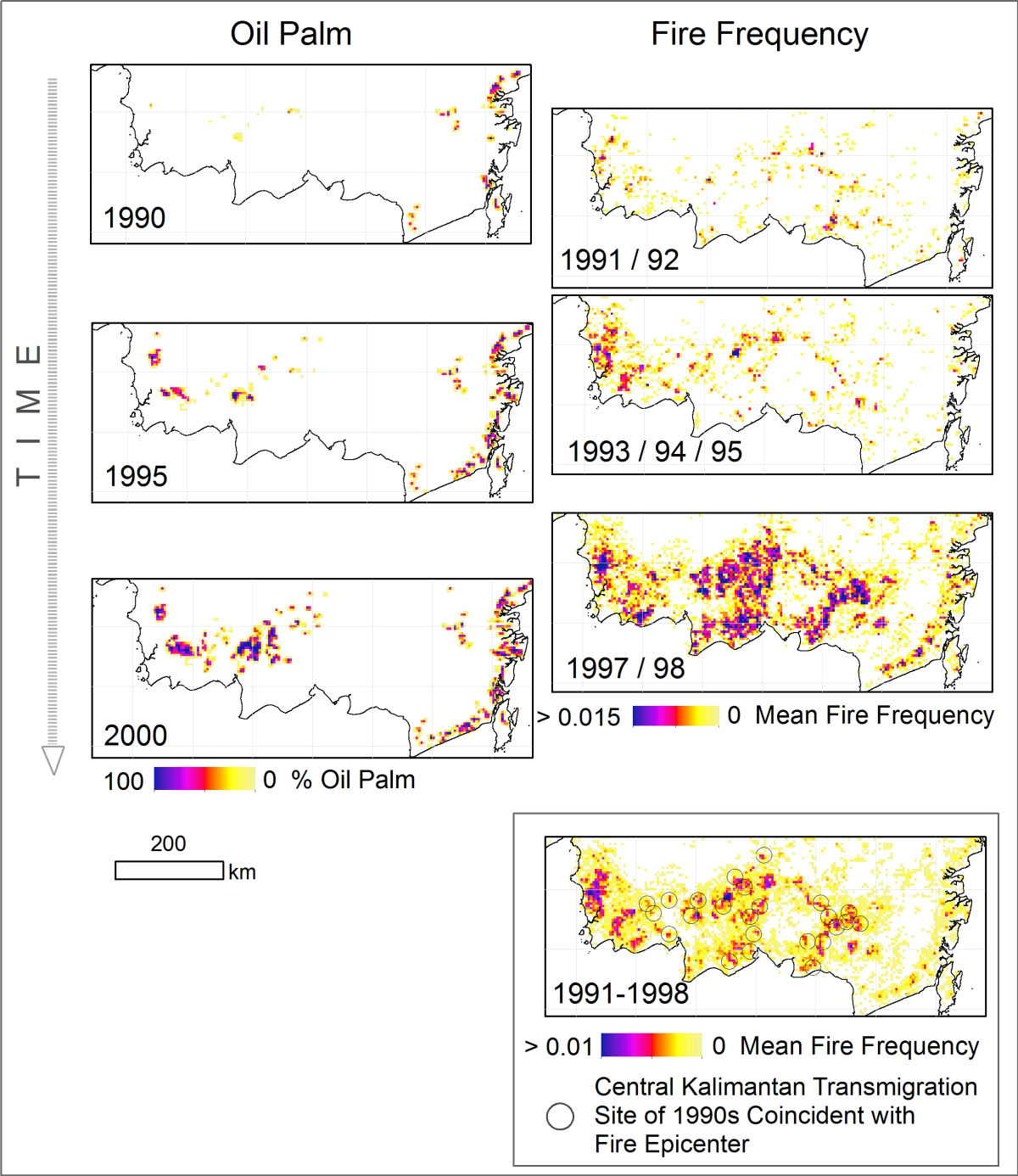
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Abstract

Tropical rainforests, naturally resistant to fire when intact, are increasingly vulnerable to burning due to ongoing forest perturbation and, possibly, climatic changes. Industrial-scale forest degradation and conversion are increasing fire occurrence, and interactions with climate anomalies such as El Niño induced droughts can magnify the extent and severity of fire activity. The influences of these factors on fire frequency in tropical forests has not been widely studied at large spatio-temporal scales at which feedbacks between fire reoccurrence and forest degradation may develop. Linkages between fire activity, industrial land use, and El Niño rainfall deficits are acute in Borneo, where the greatest tropical fire events in recorded history have apparently occurred in recent decades. Here we investigate how fire frequency in Borneo has been influenced by industrial-scale agricultural development and logging during El Niño periods by integrating long-term satellite observations between 1982 and 2010 - a period encompassing the onset, development, and consolidation of its Borneo's industrial forestry and agricultural operations as well as the full diversity of El Niño events. We record changes in fire frequency over this period by deriving the longest and most comprehensive spatio-temporal record of fire activity across Borneo using AVHRR Global Area Coverage (GAC) satellite data. Monthly fire frequency was derived from these data and modelled at 0.04° resolution via a random-forest model, which explained 56% of the monthly variation as a function of oil palm and timber plantation extent and proximity, logging intensity and proximity, human settlement, climate, forest and peatland condition, and time, observed using Landsat and similar satellite data. Oil-palm extent increased fire frequency until covering 20% of a grid cell, signalling the significant influence of early stages of plantation establishment. Heighted fire frequency was particularly acute within 10 km of oil palm, where both expanding plantation and smallholder agriculture are believed to be contributing factors. Fire frequency increased abruptly and dramatically when rainfall fell below 200 mm month⁻¹, especially as landscape perturbation increased (indicated by vegetation index data). Logging intensity had a negligible influence on fire frequency, including on peatlands, suggesting a more complex response of logged forest to burning than appreciated. Over time, the epicentres of high-frequency fires expanded from East Kalimantan (1980's) to Central and West Kalimantan (1990's), coincidentally but apparently slightly preceding oil-palm expansion, and high-frequency fires then waned in East Kalimantan and occurred only in Central and West Kalimantan (2000's). After accounting for land-cover changes and climate, our model under-estimates observed fire frequency during ca. 1990-2002 and over-estimates it thereafter, suggesting that a multi-decadal shift to industrial forest conversion and forest landscapes may have diminished the propensity for high-frequency fires in much of this globally significant tropical region since ca. 2000.

Keywords	El Niño; fire; deforestation; degradation; logging; oil palm
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Fire, Oil Palm, and Transmigration in Southern Borneo, 1990s



Fire Activity in Borneo Driven by Industrial Land Conversion and Drought During El Niño Periods, 1982-2010

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Abstract

Tropical rainforests, naturally resistant to fire when intact, are increasingly vulnerable to burning due to ongoing forest perturbation and, possibly, climatic changes. Industrial-scale forest degradation and conversion are increasing fire occurrence, and interactions with climate anomalies such as El Niño induced droughts can magnify the extent and severity of fire activity. The influences of these factors on fire frequency in tropical forests has not been widely studied at large spatio-temporal scales at which feedbacks between fire reoccurrence and forest degradation may develop. Linkages between fire activity, industrial land use, and El Niño rainfall deficits are acute in Borneo, where the greatest tropical fire events in recorded history have apparently occurred in recent decades. Here we investigate how fire frequency in Borneo has been influenced by industrial-scale agricultural development and logging during El Niño periods by integrating long-term satellite observations between 1982 and 2010 - a period encompassing the onset, development, and consolidation of its Borneo's industrial forestry and agricultural operations as well as the full diversity of El Niño events. We record changes in fire frequency over this period by deriving the longest and most comprehensive spatio-temporal record of fire activity across Borneo using AVHRR Global Area Coverage (GAC) satellite data. Monthly fire frequency was derived from these data and modelled at 0.04° resolution via a random-forest model, which explained 56% of the monthly variation as a function of oil palm and timber plantation extent and proximity, logging intensity and proximity, human settlement, climate, forest and peatland condition, and time, observed using Landsat and similar satellite data. Oil-palm extent increased fire frequency until covering 20% of a grid cell, signalling the significant influence of early stages of plantation establishment. Heighted fire frequency was particularly acute within 10 km of oil palm, where both expanding plantation and smallholder agriculture are believed to be contributing factors. Fire frequency increased abruptly and dramatically when rainfall fell below 200 mm month⁻¹, especially as landscape perturbation increased (indicated by vegetation index data). Logging intensity had a negligible influence on fire frequency, including on peatlands, suggesting a more complex response of logged forest to burning than appreciated. Over time, the epicentres of high-frequency fires expanded from East Kalimantan (1980's) to Central and West Kalimantan (1990's), coincidentally but apparently slightly preceding oil-palm expansion, and high-frequency fires then waned in East Kalimantan and occurred only in Central and West Kalimantan (2000's). After accounting for land-cover changes and climate, our model under-estimates observed fire frequency during ca. 1990-2002 and over-estimates it thereafter, suggesting that a multi-decadal shift to industrial forest conversion and forest landscapes may have diminished the propensity for high-frequency fires in much of this globally significant tropical region since ca. 2000.

Keywords: El Niño, fire, deforestation, degradation, logging, oil palm

1.0 Introduction

Humid tropical forests, naturally resistant to burning when intact, are increasingly subject to destructive landscape fires driven by agricultural expansion, forest disturbance, and potentially climate change (Cochrane, 2009; Krawchuk et al., 2009; Jolly et al., 2015). Borneo is exemplary in this respect, as there, significant periodic declines in precipitation during El Niño events associated with the positive phase of the El Niño Southern Oscillation (ENSO) climatic phenomenon have repeatedly coincided with what are generally regarded as the largest recorded tropical biomass burning events following forest degradation and agricultural development (Malingreau et al., 1985; Liew et al., 1998; Barber and Schweithelm, 2000; Siegert et al., 2001; Page et al., 2002; Field et al., 2009). Climatic projections anticipate variable, generally increasing trends in annual precipitation, but also increases in seasonal drought indices and a three-fold increase in the number of days of extreme fire danger per annum in fire-prone regions of Indonesia (Herawati and Santoso, 2011). Projections of increasingly frequent or extreme ENSO phenomena (Cai et al., 2014) and more pronounced ENSO-driven periodic precipitation reductions across the western Pacific (Power et al., 2013) presumably extending to Borneo could compound such trends and, by extension, recurrent fire activity. The 2015/16 El Niño event ranked alongside the 1997/98 and 1982/83 events in terms of extreme sea-surface temperature anomalies (Null, 2016); yet, whilst extreme by any standard (Field et al., 2016; Huijnen et al., 2016; Tacconi, 2016), observations to date suggest that the 2015/16 fires did not occur at the unprecedented scales of these historic events suggesting changing relationships between landscape fire activity, land change, and climate, as well as between precipitation and El Niño events.

Industrial-scale forest extraction, degradation, and agricultural conversion have been advanced as principal drivers of landscape burning in Borneo exacerbated by El Niño events (Leighton, 1984: 132; Lennertz and Panzer, 1984; Malingreau et al., 1985; Woods, 1989; Wirawan, 1993; Gellert, 1998; Dennis and Colfer, 2006). Despite pronounced El Niño droughts over the 19th and 20th centuries (Walsh, 1996) and gradual declines in precipitation since the mid-20th century (Malhi and Wright, 2004), major El Niño fire events appear not to have occurred in Borneo until 1982/83 (Field et al., 2009), ~10 years after industrial logging commenced and alongside ‘transmigration’ agricultural settlement (Dennis and Colfer, 2006; Gaveau et al., 2014a). Concerns over historical, ongoing and planned forest exploitation and conversion are heightened by the potential for intensifying El Niño events. Of particular concern are feedbacks between fire activity and forest degradation, such as that due to timber extraction and agricultural activities. Relative to intact forests, perturbed forests appear more prone to fire occurrence and, once burned, become still more fire-prone, so that increasingly recurrent fires in such forests may maintain them in degraded, low-vegetation states (Cochrane et al., 1999; Nepstad et al., 1999; Siegert et al., 2001; Cochrane and Laurance, 2002; Dennis and Colfer, 2006; Cochrane and Laurance, 2008). Such feedbacks have apparently converted vast areas of intact and selectively-logged forest to scrublands and fern fields in Borneo since the 1970s (Hosco et al., 2011; Gaveau et al., 2016b). In one region of East Kalimantan, many forests that burned in logged forests in 1982/83 burned again in degraded forests in 1997/98, and ultimately 70% of forests initially damaged by fire and drought in 1983 were reportedly non-forest by 2000 (Dennis and Colfer, 2006), reflecting the biophysical effects of recurrent fire as well as opportunistic oil-palm and timber plantation establishment over ‘degraded’ forests (Schindele et al., 1989). Plans to greatly expand oil-palm and timber plantations (Verchot et al., 2010; Miettinen et al., 2012a; Jakarta Post, 2014) as well as logging operations to a lesser extent in perturbed landscapes may thus threaten forest loss more widely by intensifying future fire regimes. In Sumatra, where oil palm and timber plantations on peatlands are more extensive than in Borneo, major landscape fires may no longer be confined to El Niño events (Gaveau et al., 2014b).

Shifts in El Niño - fire activity in Borneo over the last 40 years undermine historical generalisations regarding the drivers of fire reoccurrence and thus our ability to anticipate future trends. Following the 1982/83 El Niño, surveys overwhelmingly found logged or 'disturbed' lowland forests to be the most extensively burned land covers, absolutely and relatively, with 58-88% of their total area burned (Lennertz and Panzer, 1984; Leighton and Wirawan, 1985; Schindele et al., 1989; Gellert, 1998). Smallholder 'slash-and-burn' agriculture was widely considered the primary ignition source (Dennis, 1999). By the 1997/98 El Niño, recently established industrial oil-palm and timber plantations provoked new dynamics (Dennis, 1999). Estimates of burned plantation areas vary widely, from negligible to half of the area of burned logged/disturbed forests (Fuller and Fulk, 1998; KLH, 1998; Legg and Laumonier, 1999; Siegert and Hoffmann, 2000; Dennis and Colfer, 2006). The burned proportion of plantations similarly varied from the negligible to 66%, often exceeding proportions for logged/disturbed forests (Siegert and Hoffmann, 2000; Siegert et al., 2001; Dennis and Colfer, 2006). Fires arose extensively in or around plantations, in addition to other land covers (Dennis and Colfer, 2006) and ignition sources grew to include arson by expansionist concessionaires and aggrieved smallholders (Potter and Lee, 1998; Tomich et al., 1998; Dennis, 1999). Accelerated plantation expansion (Miettinen et al., 2012a; Miettinen et al., 2012b) and the decline of logging (Gaveau et al., 2014a) and agricultural transmigration programs (Potter, 2012) following decentralisation over the 2000s has quite possibly shifted patterns of El Niño fire patterns once again.

Improved understanding demands ampler spatial and temporal scales of observation than has been the case to date. Whilst important for highlighting major trends, prominent generalisations, such as that "recurrent fires will lead to a complete loss of Borneo's lowland rainforests" because 59% of observed logged forests burned in 1997/98 and some of these burned previously in 1982/83 (Siegert et al., 2001), rest somewhat tenuously on short observation periods (e.g., 2-3 months, or one inter-annual comparison) and/or analysis of relatively small geographic areas (typically severely-burned and widely degraded parts of fire-prone East Kalimantan). Further, most analyses focus only on the 1997/98 El Niño, for which exceptional drought greatly exacerbated burning across all land covers to such an extent that insight regarding fire reoccurrence are of uncertain generality (Tacconi, 2003:6; Dennis and Colfer, 2006). Syntheses of trends underlying fire activity across individual El Niño events are frustrated by inconsistent, incomplete and uncertain surveys of burned land covers (e.g., KLH, 1998; Siegert and Hoffmann, 2000; Siegert et al., 2001; Langner and Siegert, 2009), which frequently conflate 'degraded' and 'logged' forests. It is also problematic to equate the burned proportion of a land cover with its fire reoccurrence rate, particularly for severe El Niño events. Recurrence rates reflect active land-use strategies and the juxtapositions of land use/covers that propagate or experience burning differently, in addition to the inherent propensity of a given land cover to burn. Observations that 80% of El Niño fire 'hotspots' occurred within logging concessions in Kalimantan over 1997-2006 are thus qualified by the points above as well as by the facts that such forests were not necessarily contemporaneously logged and that they comprised a comparable 68% of the landscape and most of its forest extent (Langner and Siegert, 2009). Exceptional regions, particularly Malaysian Borneo, which has been widely perturbed and heavily logged (Bryan et al., 2013; Gaveau et al., 2014a) but which has experienced relatively few large landscape fires during El Niño events (Langner and Siegert, 2009; Wooster et al., 2012), further highlight the problems of generalising from short-term and regionally-confined studies.

Here we comprehensively profile the effects of industrial forest extraction and agricultural development on fire frequency across Borneo during all El Niños occurring over 1982-2010. To do so we derived the longest-term and most complete spatial record of tropical landscape fires and land-use change spanning historical ENSO episodes for a large tropical region insofar as we are aware. Our

observations encompass the onset, development, and consolidation of Borneo's industrial forestry and agricultural operations as well as the full diversity of its historical El Niño events. This allows for more confident generalisations of future El Niño-related fire reoccurrence given continued industrial land-cover change.

2.0 Methods

We modelled monthly landscape fire frequency in Borneo over 1982 - 2010 as a function of coincident industrial land use (logging, oil palm and monoculture timber plantations), forest and peatland degradation, human settlement, and climate since the 1970s. The following details our fire data, predictor variables, and modelling approach in turn.

2.1 Active Fire Mapping

To map the historical location and frequency of fire activity across Borneo we used thermal infrared imagery collected by the Advanced Very High Resolution Radiometer (AVHRR) carried aboard NOAA (National Oceanic and Atmospheric Administration) POES (Polar Orbiting Environmental Satellites). AVHRR data are collected once nightly and once daily over Borneo. Multiple POES satellites were in orbit during most years of our study, increasing our temporal sampling rate further. We processed all raw AVHRR Global Area Coverage (GAC) satellite data acquired during El Niño periods between June 1982 and June 2010 to map locations of actively burning fires across Borneo and in turn to compile the most long-term and complete spatio-temporal record of monthly fire activity for a large tropical region (**Text S1**).

The minimum detectable active fire surface area in our AVHRR GAC data ranges from ~4000 to 40,000 m², depending on the fire's exact thermal characteristics (Wooster and Strub, 2002). Sub-surface peat fires would have a greater minimum size due to their lower surface temperatures (Wooster et al., 2013). Extensive testing of GAC data confirms that they reliably capture the major spatio-temporal patterns of El Niño fire activity observable with more recently available, finer-scale satellite data, e.g., ATSR, MODIS. (**Text S1**). Our GAC fire data appear apt at capturing major fire activity associated with forest change and conversion as well as 'wildfires'. Dispersed and low-level fire activity, particularly that associated with the maintenance of smallholder agricultural plots in relatively cleared landscapes, is apparently under-estimated.

2.1.1 Observation Period

Here an El Niño event is defined by an Oceanic Niño Index (ONI) threshold of $\geq 0.5^{\circ}\text{C}$ over five consecutive months (NOAA, 2014a), signalling a positive sea-surface temperature anomaly relative to a 30-year historical average (Trenberth, 1997). Although landscape burning occurs annually in Borneo, the most extensive and prolonged fire events are confined to El Niño events (Wooster et al., 2012). Indeed, fire activity across insular Southeast Asia is, on average, seven-times greater during El Niños compared to at other times (**Figure S1**) (Van der Werf et al., 2010). Between 1997 and 2009, 78% of biomass burning in insular Southeast Asia occurred during the first calendar year of an El Niño event, with a further 15% occurring in the second year (Van der Werf et al., 2010). Our analysis of fire activity focuses on El Niño events to account for the vast majority of historical fire activity while still ensuring reliable fire detections using GAC data (**Text S1**). This approach was adopted previously by Wooster et al. (2012), but we extend it here by considering all GAC data rather than a select few scenes per month and by encompassing all El Niño events over 1982 - 2010.

Whenever the ONI was $\geq 0.5^{\circ}\text{C}$ between June of a given year and June of the next year (NOAA, 2014a) this 13-month period was selected for analysis. Typically, the ONI was $\geq 0.5^{\circ}\text{C}$ for most or all of these 13 months. This June-to-June observation period was adopted because virtually all fire activity in Borneo is confined to this period, as shown in Wooster et al. (2012: Fig.7) using GAC data for 1982/83 and our assessment of the ATSR World Fire Atlas record for 1997/1998 (ESA DUE, 2012). In two instances (June 1986-June 1988 and June 1993-June 1995) sustained ONI values of $\geq 0.5^{\circ}\text{C}$ led us to select longer 25-month periods. In total, we selected 141 months of GAC data covering the nine periods spanning 1982/83, 1986/87/88, 1991/92, 1993/94/95, 1997/98, 2002/03, 2004/05, 2006/07, and 2009/10.

2.1.2 Scene Selection, Data Pre-Processing, and Monthly Fire Frequencies

Following Wooster et al. (2012), Wooster and Strub (2002), Fuller and Murphy (2006), and Legg and Laumonier (1999), we analyzed nighttime GAC imagery exclusively in order to remove the potential for sunglint- and cloud-induced ‘false’ fire detections unrelated to fire. Nighttime data are particularly suited for mapping fires in Borneo during El Niño events because during these episodes Borneo’s fires burn for extended periods into the night and are more numerous than during the day, with fire counts peaking in the early evening (Giglio, 2007; Wooster et al., 2012). Nighttime GAC fire counts nonetheless strongly correlate with daytime GAC fire counts during El Niño events (Wooster et al., 2012: Fig.4), indicating that nighttime and daytime fire patterns are very similar. Nighttime data also allows for more sensitive active fire-detection thresholds since ambient temperatures are lower than during the day (**Text S1**). For selected GAC data, POES satellite overpass times varied between early evening (09:20-11:00 UTC) and pre-dawn (~17:00-19:45 UTC).

We selected our nighttime GAC data from the NOAA CLASS database, which archives all POES imagery (www.class.ngdc.noaa.gov). Scenes were downloaded where they were acquired during the 141 months of interest and fully contained Borneo in the scene center (an AVHRR swath is 2399 km wide with a latitudinal extent greater than that of Borneo). This minimized geometric distortion effects and maintained a more consistent pixel area between scenes. Scenes where less than 10% of Borneo was cloud free were excluded. While this cloud threshold may seem liberal, it maximised imaging sampling intensity to capture as many ephemeral fires as possible, as during gaps in cloud cover. Fire-affected lowlands in Borneo are relatively cloud free during El Niño events (see Wooster et al., 2012).

In total, 3658 GAC nighttime scenes met our selection criteria over the eighteen years listed in Section 2.1.1. Prior to active fire detection, the mid-infrared (MWIR, $3.7\text{ }\mu\text{m}$) and longwave infrared (LWIR, 11 and $12\text{ }\mu\text{m}$) channels of the nighttime GAC imagery were calibrated into brightness temperature (BT) units of Kelvin and the imagery was geometrically registered to a 0.04° spatial grid using Delaunay triangulation resampling. This 0.04° grid resolution was selected because it matched the along-scan length of an original $4.4\text{ km} \times 1.1\text{ km}$ GAC pixel (**Text S1**). The GAC nighttime active-fire detection algorithm described in Wooster et al. (2012) and already optimized for Borneo was applied to each scene, with the MWIR-LWIR BT active fire detection threshold increased from 6 K to 7.25 K following further testing in order to minimize false alarms. Each output active-fire map flagged a pixel as containing active fires (value of 1) or not (value of 0).

The 3658 separate active-fire maps resulting from this process were aggregated by month to produce 141 monthly maps of nominal or ‘raw’ monthly fire frequency. The value of a pixel in a map

of nominal monthly fire frequency corresponds to the number of observations in which that 0.04° pixel was identified as hosting an active fire during the month in question. This nominal monthly frequency was then normalized by the number of GAC scenes processed for a given month (**Figure S3**) to control for variations in the number of POES satellites operating as well as variations in cloud cover. The modelling described below pertains to normalized monthly fire frequency per pixel over the 141 months.

2.2 Drivers of Fire Reoccurrence

Our model of monthly fire frequency was developed using the 39 predictors in **Table 1**. These encompass the major factors thought to drive fire activity in Borneo and for which spatial data are available over 1982-2010. Predictors are observed per 0.04° grid cell or as fractional parts thereof. Grid cells are effectively landscapes of mixed biophysical, climatic, and land-use/cover elements, the relative effects of which on fire frequency are parsed by our model. This allows us to observe variations in the effect of a predictor as landscape composition shifts due to progressive land-use change or seasonal bioclimatic fluxuations. Parsing also allows us to observe spatial associations between fire activity and industrial land-uses where burning is not necessarily *coincident* with land use.

2.2.1 Land Cover and Land-Cover Change

Logging intensity (km logging roads per km²) and the percentage area of oil palm and timber plantations were observed per grid cell. Oil-palm and timber plantation aerial footprints were measured by visually interpreting cloud-free Landsat imagery for 1973, 1990, 1995, 2000, 2005 and 2010 (Gaveau et al., 2013; Gaveau et al., In Press), having 30-m spatial resolution or 80-m resolution before 1990. Logging roads were similarly digitized using Landsat imagery for 1973, 1990, 2000 and 2010, with additional reference to Landsat imagery of 1995 and 2005 to ensure correct interpretation. Plantation footprints and logging roads were mapped with 90% overall classification accuracy according to comparisons with high-resolution Google Earth imagery (Gaveau et al., 2014a:Table 3).

Logging-road densities and the fractional area of oil-palm and timber plantations per grid cell were extrapolated to monthly intervals to render estimates temporally concordant with our fire-frequency data. Extrapolations for a given month were made between the two closest years of observation bounding the month. Oil-palm and timber plantations observed in one year were assumed to persist over all following years of the time series. With one exception discussed below, logging roads were treated as decadal, not temporally persistent, because logged forests gradually recover a structure and microclimate prohibitive to burning (Pereira Jr et al., 2002; Asner et al., 2004; Broadbent et al., 2006).

The fractional areas of peatland and degraded peatland were also observed. Peatlands in Kalimantan are as delineated by the Ministry of Agriculture (2011), based on delineations by Wahyunto and Subagjo (2004) and virtually identical to their update (Ritung et al., 2011) described by Wahyunto et al. (2014) except that our delineation retains shallower (<50 cm) peatlands. Peatlands in Sarawak and Brunei are based a regional soil map (FAO, 2007) amended with reference a 2010 SARVISION radar-derived land-cover classification (Hoekman et al., 2010). Degraded peatlands are the area of peatland coincident with oil palm, timber plantations, and logged areas for each observation year above, with the overlap of these land covers and peatlands observed separately and in aggregate. Logged areas are <700-m from logging roads, as determined by Borneo-wide MODIS satellite observations of reduced tree cover within this distance from our logging roads (Gaveau et al., 2014a). Peatland degraded by logging was treated as temporally persistent due to the persistence of peatland degradation.

Changes to peatland condition were thus accounted for as well as possible in the absence of consistent, historical time-series data on peatland extent and condition in Borneo. Data limitations prevented any accounting of localised peatland disappearance due to exhaustive oxidation over our time series, a possibility where peatlands were converted early in our time series and were not deep ($\sim 1.9\text{--}2.5$ m). Distance from peatlands and from variously degraded peatlands were also observed and extrapolated to monthly intervals. Distances were measured at 100-m resolution and then averaged per grid cell.

Landscape perturbation was estimated using monthly normalised difference vegetation index (NDVI) data derived from AVHRR imagery (*Remote Sensing*, 2013; NASA, 2015) as well as enhanced vegetation index (EVI) data derived from combined AVHRR-MODIS imagery (Didan, 2010; VIP Lab, 2014). Landscape perturbation pertains to the degree to which the originally intact forest landscape within a grid cell has been opened, degraded, and converted to non-forest land covers, as by human settlement, forest fragmentation, agriculture or burning, all of which are expected to depress vegetation indices. Low monthly index values may also reflect seasonal cycles of vegetation vigour (Meneses-Tovar, 2012), but in a manner complementary to our interpretation of landscape perturbation. Whereas fire frequency tracks index values over a wide range, from high to low index values indicative of perturbation (see Results in Section 3.3.2), seasonal variations in index values are comparatively wide in landscapes that are evidently perturbed. In such landscapes, very low index values manifest as low dry-season precipitation dries vegetation more severely than in relatively intact landscapes.

Direct measures of smallholder agriculture were not available over our full time-series for Borneo. As a proxy, our model includes measures of the distance from oil-palm plantations, timber plantations, and logging roads for a given year following observations that smallholder activity occurs widely within and around plantation concessions (Gaveau et al., 2014b; Lee et al., 2014; Gaveau et al., 2016a; Wijedasa et al., In Press). Distances were calculated and extrapolated to monthly intervals as above.

To explore smallholder agricultural activity in relation to industrial plantations and fire activity more directly, we also directly observed the expansion of smallholder agricultural activity around oil-palm plantations on peatlands since 1990. This analysis was separate from the Borneo-wide modelling for 1982-2010 because data on smallholder activity were confined to peatlands and were available only since 1990. This analysis informs modelled observations of heightened fire activity in proximity to oil-palm plantations (Section 3.3.1). Areas of smallholder agriculture and pristine forests on peatlands in 1990 and 2008, delineated via visual interpretation of Landsat and SPOT imagery (Miettinen and Liew, 2010), were expressed as percentages of buffer areas surrounding oil-palm plantations observed in 1990 and 2010, respectively. Buffers were defined concentrically in 1-km intervals and were similarly confined to peatlands. Since oil palm on peatlands in 1990 was concentrated in northern Sabah and West Kalimantan, in contrast to its broader distribution by 2010, we observed smallholder and pristine-forest areas of 2008 around plantations of 2010 in two ways: (i) all oil-palm plantations on peatlands in 2010 were considered, and (ii) only plantations on peatlands in 2010 that are within two km of plantations on peatlands in 1990 were considered. This latter ‘fixed’ extent of observation allows for more consistent assessments of the change to smallholder and pristine-forest area around plantations over 1990-2008, but it is narrowly confined to the peatlands of northern Sabah and West Kalimantan.

2.2.3 Climate

Historical precipitation and temperature were assessed at one, two, three and four-month intervals preceding and inclusive of a given month, interpolated from weather stations to a 0.5° grid (CRU et al.,

2014; Harris et al., 2014). This staggered temporal resolution allowed us to capture climatic effects on fire activity both where dry seasons are long and unimodal, as in Southern Kalimantan, and where they are short and bimodal, as in East Kalimantan (Aldrian and Dwi Susanto, 2003; Field and Shen, 2008; Gaveau et al., 2014b). Our model also included historic average monthly precipitation and temperature relative to a 30-year period (1961-1990). Separate reference below is also made below to ‘MOD16A2’ data on monthly potential evapo-transpiration (PET), estimated using 1-km MODIS and other satellite data by Mu et al. (2011). We observed average June PET values over 2000-2014, where June was selected because it is onset of the dry season across fire-affected East and Central Kalimantan.

2.2.4 Time, Human Settlement, Landscape Accessibility and Management

Our model of fire frequency included predictors for the passage of time, settlement intensity, landscape accessibility, and forest-management regime proxies, since these were considered likely to vary the effects of the aforementioned predictors. The passage of time is the number of months elapsed since June 1982 – the start of our fire record and the first time a major El Niño fire event is recorded in Borneo (Malingreau et al., 1985). Settlement and accessibility are defined variously by population density, extrapolated to monthly intervals from observations in 1990 and 2000 (CIESIN, 2011); by the maximum electric nightlight brightness observed over 1996-2010 by the DMSP-OLS satellite sensor (NOAA, 2014b), averaged over 15 km, 30 km, 50 km and 100 km radii to account for proximate extra-urban settlement dynamics; by distance to inter-urban roadways (NIMA, 2000); and by topography (elevation, slope, and aspect per grid cell) according to the SRTM 90-m digital elevation model (Jarvis et al., 2008). Finally, we include two categorical variables coding for the country and administrative region of a grid cell following observations that fire activity varies significantly between parts of Malaysian and Indonesian Borneo (Wooster et al., 2012:Fig.8), possibly reflecting differing forest management practices (Murdiyarso and Adiningsih, 2007).

2.3 Modelling Fire Frequency

A random-forest model predicting fire frequency was developed using the R packages *randomForest* and *forestFloor* (Liaw, 2015; Welling, 2016). Our initial dataset was comprised of 35,517 grid cells over 141 months, or ~5.3 million ‘voxels’ (i.e., grid cell c of month m), only a small fraction of which actually contained fires. To avoid autocorrelation effects, which are not problematic in random-forest modelling, we analysed voxels separated from each other by at least one month or four grid cells. This sampling, which was determined iteratively, greatly reduced the Moran’s I index of autocorrelation relative to that of the complete dataset while still retaining a sizable sample. We randomly and iteratively selected fire voxels subject to these restrictions until no more fire voxels were available, ultimately sampling 5,358 fire voxels. The same number of non-fire voxels were randomly and iteratively selected, for a total of 10,716 voxels. The equal inclusion of fire and non-fire voxels enhances model robustness and generalisability. The specific response variable predicted by the model is log-transformed normalised monthly fire frequency per voxel, given as $\text{Ln}(1+100*\text{normalized monthly fire frequency})$. Log transformation served to minimize the effect of outliers.

Three model outputs describe the effect of the predictors on fire frequency. The first, variable importance scores, report the relative importance of a predictor. The measure is the percentage change to the model mean square error (MSE) upon randomly permuting a predictor’s values (Text S2). We observe the variability of our variable importance scores across 100 separate random-forest models, each entailing 100 bootstrap samples, following observations that model error declined to an asymptote as the number of samples approached 100. The second output, bi-variate feature contribution plots (FC), are graphical decompositions of our model into additive components showing the effect of a

predictor on fire frequency over its range of values. The third output, tri-variate partial dependence plots (PDPs), capture interactive effects of predictors on fire frequency, showing fire frequency for all joint values of two predictors. Both the FC plots and the PDP plots identify critical values of predictors beyond which fire frequencies change abruptly (Palczewska et al., 2014). While the trend and relative range of plotted fire frequencies are informative, the absolute values of plotted frequencies in FC and PDP plots should be interpreted with caution because they are adjusted by model decomposition. Text S2 provides supplementary details on the model.

3.0 Results

3.1 General Spatio-Temporal Trends

Monthly fire frequency was highly variable over space and time between 1982 and 2010. Fire frequency clustered regionally, especially in Central and East Kalimantan, but also varied greatly within these regions (**Figure 1**). Short-term cycles in fire activity were punctuated by occasional extremes, and in general the temporal profiles of fire frequency were only moderately comparable across individual El Niño periods (**Figure 2**). The mean and maximum fire frequency observed per grid cell during 1982-2010 exhibited exponentially decreasing frequency distributions with long tails of very high but rarely occurring values (**Figure 3**). Fewer than 10% of fire-affected grid cells experienced >3 landscape fires in a given month (equivalent to a normalised frequency of 0.105, **Table 2**).

When aggregated over all grid cells in Borneo on a monthly basis, fire frequency was disproportionately high relative to the number of fire-affected grid cells during the peaks of 1982, 1983, 1994, 1998 and 2002 (**Figure 2**). These years correspond to relatively severe periods of burning and marked climatic anomalies, although the relationship between fire frequency and fire-affected grid cells on the one hand and the ONI on the other is not straightforward. In terms of ONI values, the 1997/98 and 1982/83 El Niño events are respectively the first and second strongest (prior to the comparable 2015 El Niño) (Null, 2016), but 1997 alone did not exhibit the aforementioned disproportionality between fire frequency and the number of fire-affected grid cells. Further, the third, fourth, and fifth strongest El Niños in terms of the ONI either did not exhibit this disproportionality or did so moderately (2009), whilst the sixth strongest in terms of the ONI did (2002/03). The 1994 El Niño had a relatively moderate ONI but its fire frequency in **Figure 2** was still highly disproportionate to its number of fire-affected grid cells, not unlike the extreme El Niños of 1982/83 and 1997/98, perhaps reflecting the fact that the 1994 El Niño was characterised by extensive and severe burning according to finer-scale surveys (Dennis, 1999).

Our model of monthly fire frequency during El Niño periods of 1982-2010 had a predictive accuracy (as measured by the coefficient of variation; r^2) of 56.4%. **Figure 4** presents the importance scores of our predictors of monthly fire frequency, and **Figure 5** plots of the relationships between these predictors and monthly fire frequency. As seen, three general themes underlie the drivers of fire frequency in Borneo: short-term low precipitation levels, oil palm and timber plantations, and the passage of time. Each theme is discussed below.

3.2 Climate and Fire Frequency

The FC plots of **Figure 5** clearly define a critical precipitation threshold of ~ 200 mm beneath which fire frequency abruptly increases. For monthly, three-monthly and two-monthly average precipitation

variables (Clim_P1mo, Clim_P3mo, Clim_P2mo), fire frequency increased sharply as average monthly precipitation declined from 200 mm to 100 mm. These predictors were the third, fifth and eighth most important in our model, respectively (**Figure 4**). Virtually all of the effect of precipitation occurred within the narrow range of 100-200 mm. The effect was highly non-linear: neither declines in precipitation below 100 mm, nor increases above 200 mm, conferred further increases or decreases to fire frequency, respectively.

This effect is suggestive of forest drying due to anomalously low precipitation. Monthly precipitation of < 200 mm is beneath monthly historical averages for most of Borneo (Wooster et al., 2012: Fig.7a; CRU et al., 2014), approximates historical average dry-season precipitation lows in the drier, fire-affected areas of East and Central Kalimantan (CRU et al., 2014), and nears equivalency with average June potential evapo-transpiration levels of ~120-150 mm for 2000-2014 in these provinces (Mu et al., 2011). Air temperature, a factor of potential evapo-transpiration, had only a moderate predictive importance according to our model (**Figure 4**).

Figure 6 maps values of an index of disposition towards higher frequency El Niño fires due to short-term critically low precipitation levels. The index is defined by the weighted mean proportion of monthly, three-monthly and two-monthly observations with <200 mm average precipitation during the 141 months of observation, where weights are proportional to variable importance scores of these precipitation variables (**Figure 4**). The index corresponds well to the distribution of fire frequency in **Figure 1**. However, the correspondence is weaker in western Central Kalimantan, central West Kalimantan and to a lesser extent Sabah, indicating the important, additional role of land-cover change.

3.3 Land-Cover Change and Fire Frequency

Land-cover change dynamics were important determinants of fire frequency. However, except for the extent of oil-palm plantations, direct measures of industrial plantation area or logging intensity were amongst the least important predictors, including when observed exclusively on peatlands (**Figure 4**). Our model instead points to land-use dynamics centred on, but distinct from, industrial land uses.

3.3.1 Industrial Plantations and Surrounding Areas

Land-use dynamics nearby, but distinct from, oil palm and timber plantations are major predictors of high fire frequency during El Niño periods. Two observations from our model support this assertion. First, the proximity to oil palm or timber plantations always has a much greater effect on fire frequency than does the actual extent of these industrial plantation types (**Figure 4**). Second, the effect of proximity to oil-palm plantations declines quickly with distance, indicating that industrial plantations are at the heart of this effect. Fire frequency peaks at ~ 4 km distance from oil palm plantations (**Figure 5 panel 'Dist_OilPalm'**), where plantations account for 33% of grid cells' area on average (std. dev. 34%) as of 2010 (**Figure S5**) and so inter-mix closely within grid cells with non-industrial land uses/covers, particularly smallholder agriculture. By ~10 km distance from oil palm, fire frequency declines to an asymptotic low.

Increases in smallholder activity and decreases in intact forests are coincident with the heightened fire frequency surrounding oil-palm plantations. Over 1990-2008 smallholders on peatlands occupied increasing proportions of landscapes within 10-km of oil-palm plantations on peatlands, rising from ~5-10% in 1990 to ~10-20% by 2008, while pristine peat forests declined markedly from 20-35% to <1% (**Figure 7**). However, by 2008 smallholder activity was relatively constant with increasing distance from plantations (**Figure 7**) while predicted fire frequency declines sharply with distance

(**Figure 5 panel ‘Dist_OilPalm’**). This suggests that the heightened fire frequency observed nearby plantations is not a function of smallholder activity per se but rather is reflective of interactions between industrial land uses and nearby industrially-aligned smallholder activity, e.g., sharecropping, increasing agricultural settlement, infrastructure development. Fire frequency is similarly elevated around timber plantations, but only to ~5 km distance (**Figure 5 panel ‘Dist_Timber’**), and the effect is smaller than for oil-palm plantations (**Figure 4**)

The extent of oil-palm plantations was the sole industrial land use to meaningfully influence fire frequency (**Figure 4**). Virtually all the effect of oil-palm extent occurs as oil-palm coverage expands from nil to 20% of a grid cell (**Figure 5 panel ‘Land_OilPalm’**). This coverage is not particularly extensive in Borneo – 63% of grid cells containing oil palm in 2010 had greater coverage. Oil-palm expansion beyond 20% coverage yields only modest and gradual increases in fire frequency on average. This indicates that even ‘small’ extents of oil palm – including perhaps especially those established during early phases of plantation development – significantly and disproportionately enhance fire frequency.

3.3.2 Logging

Logging intensity per grid cell had a negligible effect on fire frequency. The importance scores of logging intensity generally and on peatlands were 32nd and 37th out of 39 predictors, respectively (**Figure 4**). This interpretation is supported by discounting potential alternative explanations of the negligible effect of logging intensity. The negligible effect is not attributable to a lack of forest degradation following logging. Reduced tree cover was readily apparent up to ~500 m from our logging roads in satellite imagery acquired one year after logging roads were first observed (Gaveau et al., 2014a: Figure 4). Nor is the negligible effect attributable to a weak relationship between landscape perturbation and fire frequency. Landscape perturbation, as indicated by lower NDVI values, had a clear and significant positive effect on fire frequency (**Figure 4, Figure 5 panel ‘Vege_NDVI’**). Nor again is the negligible effect attributable to a lack of coincidence between logging and areas climatically disposed towards higher frequency fires. Logging occurred over all levels of the index of disposition towards higher frequency fires due to short-term critically low precipitation (**Figure S6**). Logging intensity did not interact with monthly precipitation to effect fire frequency, whereas NDVI and precipitation did interactively effect fire frequency when precipitation was <200 mm and landscape perturbation intermediate (NDVI of ~0.5-0.7) (**Figure S7**).

3.4 Spatial and Temporal Shifts in Fire Dynamics

Epicentres of high fire frequency in Borneo during El Niño periods have shifted since 1982. High average monthly fire frequency concentrated in East Kalimantan during the 1980s, then in East Kalimantan as well as Central, eastern South, and eastern West Kalimantan during the 1990s, but by the 2000s only Central Kalimantan exhibited elevated fire frequency (**Figure 8**). The onset of higher-frequency fires in Central, South and West Kalimantan over 1991-1995 was consistently offset from areas logged as of 1990, and narrowly preceded the establishment of oil palm plantations. In 1990, oil palm was largely absent from these regions except in South Kalimantan, and by 1995 oil palm had attained a modest and patchy regional distribution, albeit one aligned with the epicentres of fire activity of 1991-1995 (**Figure 9**). By 2000, a wider oil-palm distribution nested neatly within an even wider distribution of fire activity, and oil-palm plantations concentrated where high-frequency fires were initially and persistently apparent over the 1990s (**Figure 9**). Thus, although the temporal resolution of our data precludes a precise chronology, oil palm plantations appear to be a factor, but not the leading edge, of the southern migration of high-frequency fires over the 1990s. A coincidence between

epicentres of high-frequency fire in **Figure 9** and transmigration sites established in Central Kalimantan over the 1990s (Potter, 2012), which were typically associated with oil-palm production, suggests not only an additional factor of elevated fire frequency but also a plausible causal dynamic whereby transmigrant settlements were increasingly incorporated into landscapes of industrial oil-palm production.

The exact dynamics underlying the waning of fire frequency in East Kalimantan after 2000 are not entirely known. Shifting precipitation in East Kalimantan may however partially explain the waning of fire frequency there. Greater mean precipitation in East Kalimantan ($\sim +10\text{-}25\text{ mm mo}^{-1}$) during February-April observation months in the 2000s compared to the same months during the 1990s and 1980s suggests a reduction of El Niño drying there over the 2000s (**Figure S8**). This increment of $\sim +10\text{-}25\text{ mm}$ is small absolutely but large compared to coastal Borneo, as Central and South Kalimantan registered declines in February-April precipitation over the 2000s relative to the 1990s and 1980s (**Figure S8**). During the February-April interval, pronounced ‘phase two’ fire activity occurred in the second calendar year of the extreme El Niños of 1982/83 and 1997/98 as well as for two of three other El Niño observation periods of the 1980s and 1990s (**Figure 2**). After 2000, El Niño fire activity largely concentrated in the first year of each El Niño period (**Figure 2**), consistent with increased February-April precipitation in East Kalimantan.

Additional insights into this waning of fire activity may be derived from the overwhelmingly important, non-linear effect of the passage of time (**Figure 4**). For Borneo generally, from the late 1980s to the 1990s fire frequency was increasingly greater-than-expected after accounting for contemporary explanatory factors (**Figure 5 panel ‘Time’**). Over the 2000s, fire frequency became less-than-expected again, reverting to pre-1990s trends (**Figure 5 ‘Time’**). This succession of over-prediction, under-prediction, and over-prediction of fire frequencies across three decades is suggestive of shifting relationships between fire frequency and its predictors over time. Since our model already accounts for contemporary climate and land change, other, less tangible factors moderating fire activity in East Kalimantan and elsewhere after 2000 are likely at play, potentially including shifts in forest management, landscape composition, and development cycles, as discussed below.

4.0 Discussion and Interpretation

Borneo is subject to annual fire activity, but extreme fire events occur almost exclusively during dry periods accompanying El Niño events (**Text S1**). Climatic projections anticipate more frequent extreme El Niños (Cai et al., 2014) and more pronounced associated periodic precipitation declines in the western Pacific region (Power et al., 2013), exacerbating projected ‘baseline’ increases to seasonal drought indices and three-fold increases in the number of days of extreme fire danger per annum in fire-prone regions of Indonesia (Herawati and Santoso, 2011). Increases in the frequency, extent, and intensity of El Niño fire activity could promote feedback dynamics between forest degradation and recurrent fires over successive El Niños, potentially maintaining forests in fire-prone regions in states of persistent degradation. The likelihood of, and thresholds for, such a feedback dynamic remain uncertain, however. The El Niño of 2015/16 was as strong as the extreme 1997/98 El Niño in terms of its Oceanic Niño Index (ONI) (Null, 2016); yet, whilst the 2015/16 event did coincide with extreme biomass burning with correspondent emissions of air pollutants and greenhouse gases, its magnitude of the fire activity and emissions appears notably less than those of 1997/98 (Huijnen et al., 2016;

Tacconi, 2016). Such variation underscores both the changing role of non-climatic factors such as land use/cover as well as the variable response of precipitation to El Niño events.

Our observations clarify the effect of non-climatic factors on fire frequency alongside those of climatic variability. Our model identifies 200 mm month⁻¹ as a critical precipitation threshold beneath which fire frequency rapidly increases, particularly where landscape perturbation is moderate (NDVI of ~0.5). This threshold is double that advanced by Goldammer (2007) in relation to ‘significant fire activity’, but it and its highly non-linear form are corroborated by data from Field et al. (2016) concerning the rapid onset of fire-related ‘haze’ and fire activity in Kalimantan. Regarding industrial land uses, only oil palm had a direct influence on fire frequency. Its effect predominated at modest levels of oil-palm coverage indicative of mixed-use landscapes and early-stage plantation development. More relevant still are the land-change dynamics surrounding oil-palm plantations in which smallholders apparently play a role, blurring the line of agency between industrial and local actors. Following the expansion of high-frequency fires to southern Kalimantan during the 1990s, fire frequency appears to have waned since the early 2000s in Eastern Kalimantan. Such waning possibly indicates a new phase of industrial land change and slightly greater February-April El Niño precipitation after ca. 2000. For Kalimantan, Field et al. (2016) infer an intensification of El Niño burning due to land use after ca. 2000 because fire haze was worse in 2002, 2006 and 2016 than for 1991 and 1994 despite comparable or slightly greater precipitation. Such a trend is consistent with the progressive expansion of industrial land use since ca. 1990, amongst other factors.

4.1 The Past and Future of Borneo’s El Niño Fires

A key finding is that fire frequency was much greater than predicted by our model during ~1990-2002 and less than predicted thereafter. This trend suggests that the *propensity* for heightened fire frequency was elevated over the 1990s but declined over the 2000s. It is unlikely that this decline is attributable to enhancements in fire and forest management during the 2000s. Goldammer’s (2007:27) dismissive appraisal of Indonesian fire management over the 1990s remains applicable to the 2000s (Edwards, 2015). Further, enhancements to fire and forest management over the 2000s alone would not explain the greater-than-expected fire frequency over ca. 1990-2002. The dynamics shaping this non-linear trend in fire frequency encompass both the unobserved and the intangible beyond the scope of this study.

The non-linear trend in fire frequency may reflect the oil-palm sector’s transition through a pioneer stage during the 1990s and the progressive deforestation of landscapes hosting plantations. During the 1990s, applications to convert forest to oil palm greatly exceeded the area of degraded forests designated for conversion, and so oil palm and related burning frequently incurred in relatively forested ‘permanent’ production forests (Potter and Lee, 1998). Strategic burning and over-exploitation of forests were also practiced as means of degrading forests to encourage their conversion, particularly in Central Kalimantan (Potter and Lee, 1998; Dennis et al., 2005). Such practices would have elevated fire frequency but, over the longer term, as landscapes hosting plantations retained progressively less forest cover, the propensity for fire activity would likely have diminished. Our observations in **Figure 7** as well as those of Miettinen et al. (2012a: Table 4) illustrate drastic reductions in forest cover immediately around and prior to plantations establishment between 1990 and the 2000s. These reductions of forest over the course of plantation development were most pronounced in East Kalimantan and Sabah, in part reflecting the deforestation caused by the 1997/98 fires, and it is in such regions that fire reoccurrence waned most since 1990 (**Figure 8**).

The non-linear trend in fire frequency as well as the southern migration of high-frequency fire events after 1990 may also reflect trends in transmigration. Transmigration schemes resettled smallholders from populous regions such as Java to Kalimantan until the early 2000s, after which the program was significantly reduced and reoriented toward agro-industrial labour supply (Potter, 2012). Many, if not most, of Central Kalimantan's epicentres of elevated fire frequency over the 1990s are coincident with transmigration areas established over the 1990s (**Figure 9**) (Land Resources Department/Bina Program, 1990; Potter, 2012), including notably those of the 'Mega Rice' project in the eastern peatlands, which became a perennial source of fire (Hoscilo et al., 2011). By design, transmigrant agricultural production and labour were frequently integrated into industrial-plantation landscapes (Fearnside, 1997; Cramb and Curry, 2012; Potter, 2012). The vast majority of transmigration sites in Central Kalimantan (as well as Western Kalimantan) since 1988 were Nucleus Estate Settlements (also known as PIR-Trans Settlements), characterised by cooperative arrangements between oil-palm companies and transmigrants whereby companies establish a nucleus estate and support associated transmigrant oil-palm production (Fearnside, 1997: 577). It is therefore of interest that over the 2000s industrial-scale plantations increasingly predominated in these transmigration landscapes of Central Kalimantan (Gaveau et al., 2016b: Fig.1b), presumably intermixed with transmigrant smallholders and labourers, thus yielding the very kind of landscape corresponding with heightened fire frequently.

4.2 Logging and Fire Activity

Our findings challenge inferences – strongly based on the exceptional 1997/98 fires – that logging has *generally* provoked widespread fire reoccurrence during El Niño events. A number qualifications help reconcile our observations with the literature and suggest areas for further research.

First, we observe fire reoccurrence at monthly intervals, and it is possible that logging may enhance reoccurrence only over much longer intervals, such as between El Niño events, but this has yet to be comprehensively determined for Borneo at large spatio-temporal scales. Second, large-scale aerial surveys of land cover and landscape burning in Borneo have focused overwhelmingly on burned area per land cover (Langner and Siegert, 2009). It does not necessarily follow that a land use/cover such as 'degraded/logged forests' that burns relatively extensively in aggregate also burns relatively recurrently at the local scale (e.g., grid cell). Third, in contrast to much of the literature (Langner et al., 2007), we observed logging intensity as a continuous metric and distinguished it from more generalised and extensive 'degraded forest'. The negligible effect of logging intensity on fire frequency per grid cell may simple reflect the weakness of a correlation, non-linear or otherwise, which does not necessarily preclude the possibility of a simpler association. Fourth, again in contrast to much of the literature, our observations are inclusive of all of Borneo over three decades, not focused on specific, fire-prone regions wherein forest degradation and land-use change were contemporaneous with an extreme El Niño event (Siegert et al., 2001; Page et al., 2002). Thus the 'average' effects we describe should temper extrapolations from such regional case studies but not be used to dismiss them per se. Finally, our GAC fire data may have under-estimated fire activity within or immediately adjacent to logged forests where such fires were small, dispersed, or ephemeral (**Text S1**). Also, 'scale effects' could have dampened the apparent association between logging intensity and fire frequency where logging roads were sparse within grid cells. Both these possibilities are considered to be of moderate potential effect, if not unlikely, since fires in logged/degraded forests are expected to be relatively large and hot while logging intensity ranged widely across our grid cells.

Our observations support views that since the mid-1990s Borneo has been transitioning to a fire regime increasingly driven by industrial plantations. Logging activity has contracted by at least 50% over the 2000s relative to its peak in the early 1990s (Ministry of Forestry, 2012; Gaveau et al., 2014a). Over the same period, oil-palm and timber plantations expanded massively (Verchot et al., 2010; Miettinen et al., 2012a; Ministry of Forestry, 2012) and, as our model shows, associated far more strongly with fire frequency.

4.3 Industrial vs. Smallholder Contributions to El Niño Fire Frequency

The predominant land-change dynamics heightening fire frequency are those immediately surrounding oil palm (**Figure S9**). This pattern points to dynamics that likely integrate both industrial agricultural and smallholder agents. The degree to which each agent is responsible for fires remains unclear given their proximity to each other, limited data on smallholders, and the conflation of fire ignition, occurrence, reoccurrence, and burned area in the literature (Tacconi, 2003; Vayda, 2006; Cattau et al., 2016). Even still, in response to severe burning during 2015, the Indonesian government is undertaking a ‘fire-free village program’ in approximately 730 smallholder settlements, following community fire-prevention models originally developed by industrial plantation interests.

Heightened fire frequency around oil-palm plantations likely partly reflects the stimulation of economic activity and local smallholder agriculture by industrial plantation development. Plantations require one labourer for each 4-6 ha of oil palm, in addition to roads, mills, settlements and other infrastructure, all of which generate an economic gravity for non-industrial agents of landscape change. Our analysis show that smallholder-dominated areas expanded appreciatively around oil-palm plantations over 1990-2010 (**Figure 7**), while others observe smallholder agriculturalists to occupy ~19-32% of oil-palm concessions (Gaveau et al., 2016a; Wijedasa et al., In Press).

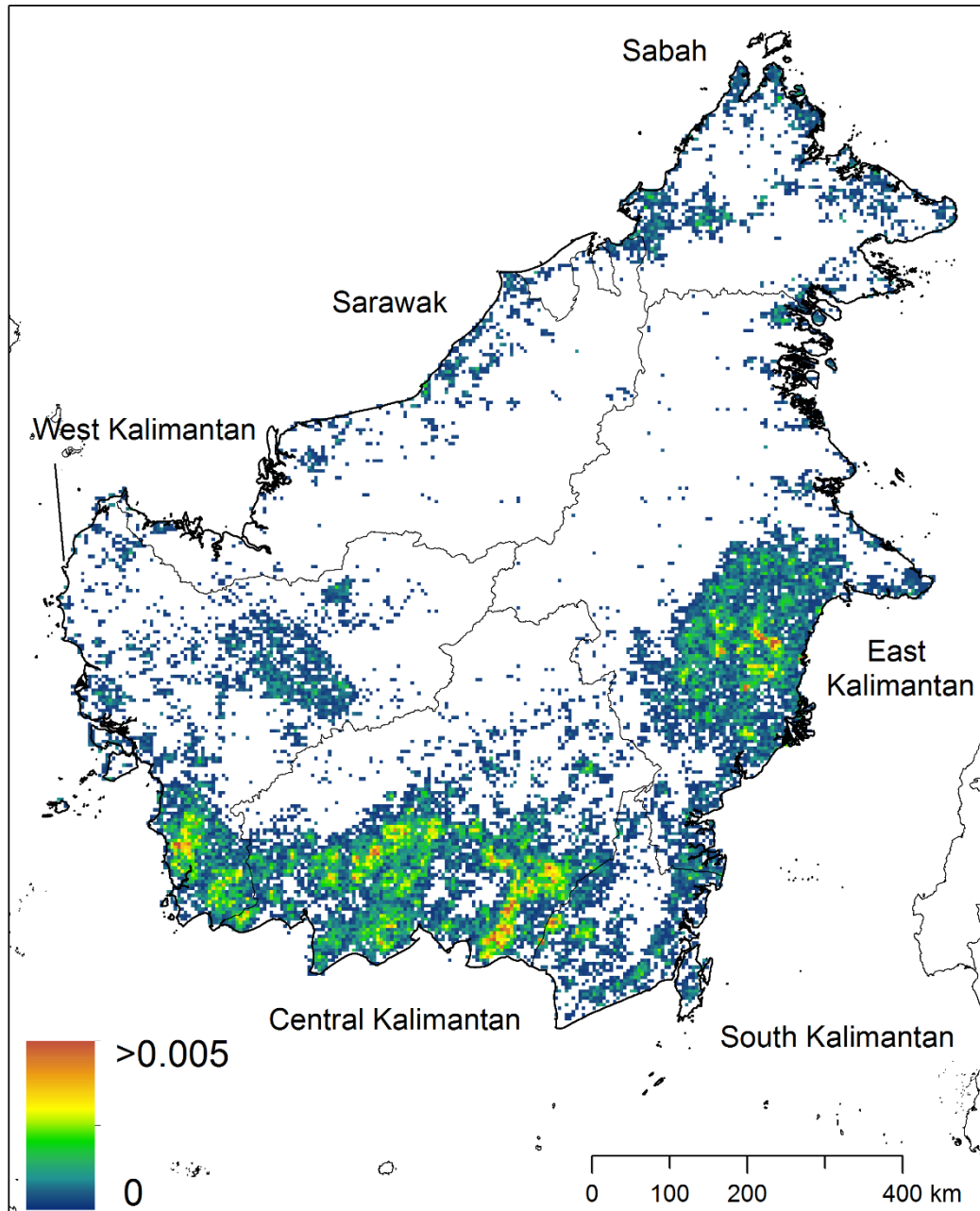
Concessionaires’ strategic or careless use of fire to expand landholdings and clear lands would certainly also account for heightened fires frequency around oil-palm plantations. This activity, also exploited by smallholders during droughts, is realised by concessionaires using share-croppers or migrant labour (Potter and Lee, 1998; Dennis, 1999; Barber and Schweithelm, 2000; Ekadinata et al., 2013). The veracity of this interpretation is supported by observations from Riau, Sumatra during its major 2013 fire event (Ekadinata et al., 2013). There, in the context of an expansionary oil-palm sector known to integrate smallholders (Gaveau et al., 2014b), the odds of fire occurrence at a given distance from oil-palm concessions defined a curve nearly identical to our plot of fire frequency vs. distances from oil palm (**Figure 5 panel ‘Dist_OilPalm’**), including its peak in fire activity at ~3-5 km distance. Cattau et al. (2016) also observed a nearly identical curve for the Mega Rice Project area of Central Kalimantan, where transmigrant settlements border oil-palm concessions.

The implication that industrial plantations heighten fire activity in part by stimulating smallholders, migrant labour, and economic growth is consistent with an emergent view that industrial land change in insular Southeast Asia is neither the greatest nor even an independent force for forest destruction. Reports that Indonesian concessionaires have converted more forest and emitted more carbon than smallholders (Lee et al., 2014) have for example been upset by estimates sensitive to smallholders’ interactions with concessionaires (Gaveau et al., 2014b; Gaveau et al., 2016a; Wijedasa et al., In Press). Our observations challenge the conservation-science community to broaden its long-standing fixation on the readily visible, culturally unpopular ‘corporate’ concessionaires (Koh et al., 2011; Lee et al., 2014; Abood et al., 2015). We encourage greater emphasis on the more nuanced

690 dynamics of economic interaction and spatial dependence between concessionaires and non-industrial
691 agents of change.
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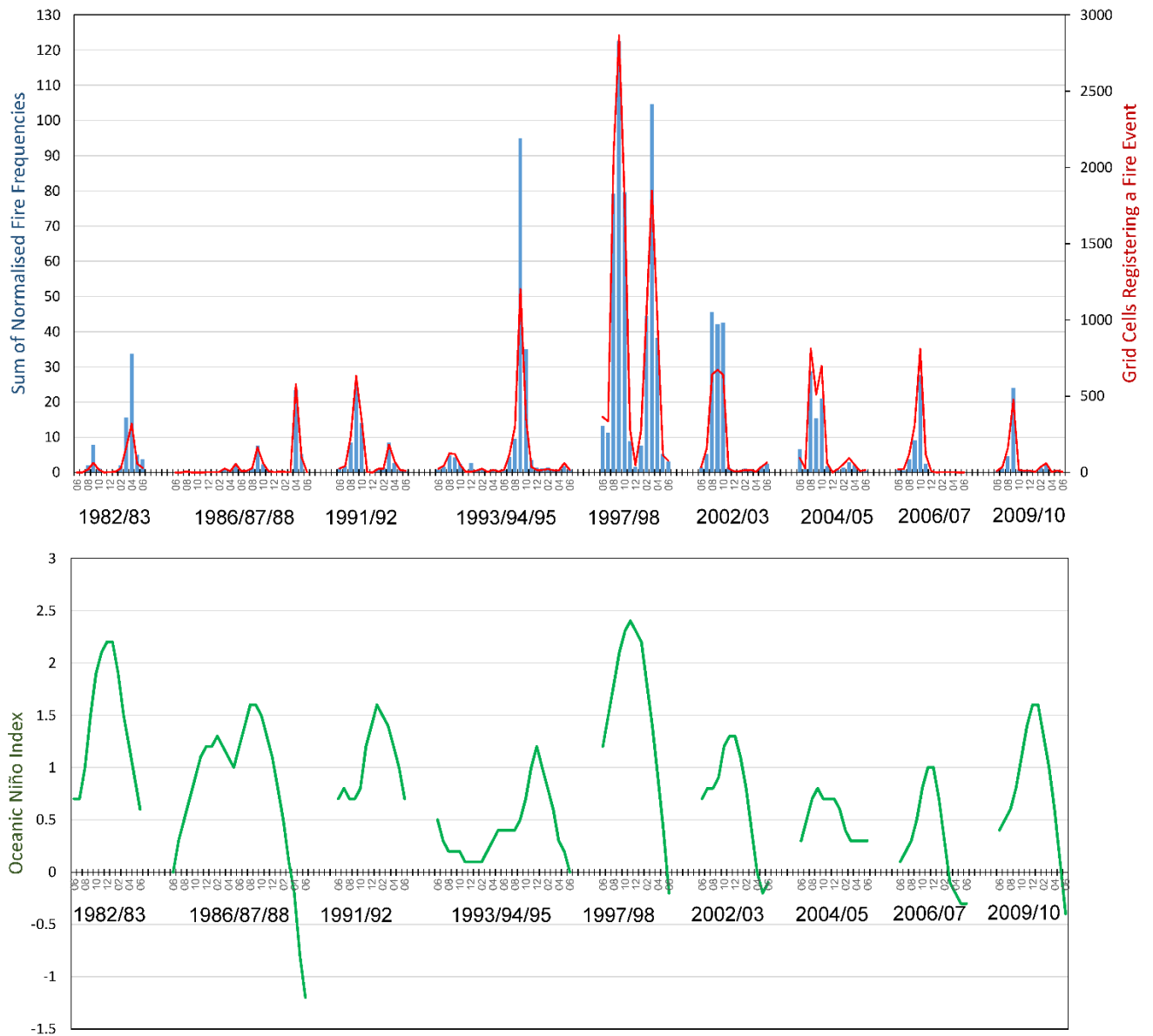
Figures

Figure 1 –Mean normalised monthly fire frequency, El Niño periods of 1982-2010.



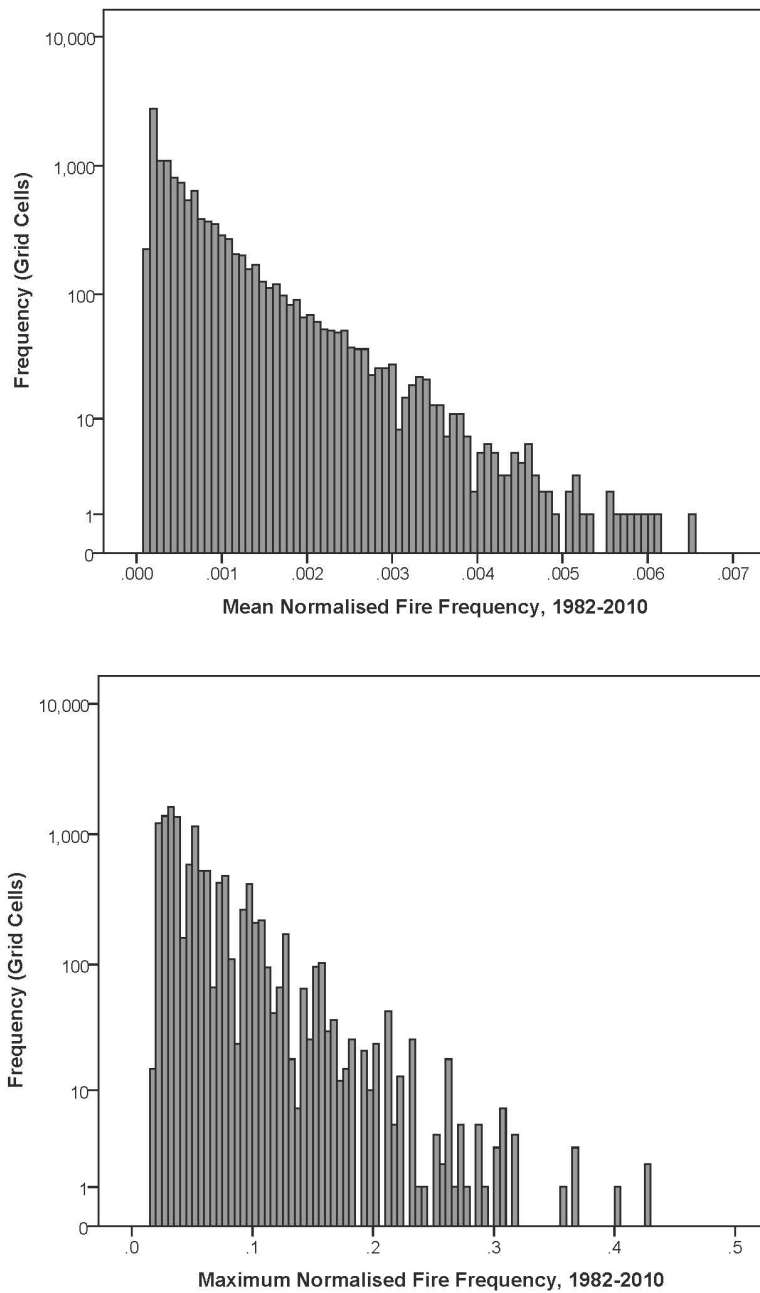
Notes: Mean normalised monthly fire frequency calculated from the 141 months of observation spanning all El Niños of 1982-2010. The actual maximum normalised monthly mean value is 0.0071, but the legend sets the maximum to >0.005 for greater image contrast. See **Figure S4** for total monthly nominal fire frequency for El Niño fire events over 1982-2010.

Figure 2 – Monthly fire frequency and Oceanic Niño Index, by month, El Niño periods of 1982-2010.



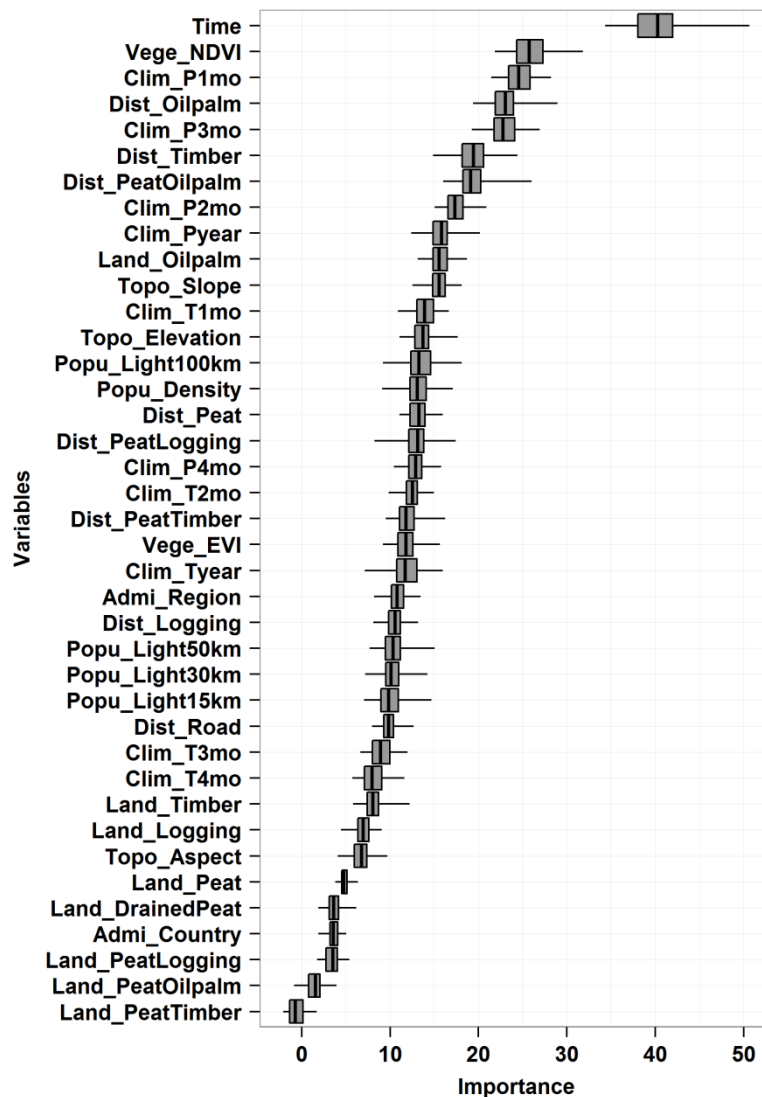
Note: Labels on the x-axes denote every second month, where 01 and 12 denote January and December, respectively (n=141 months). Blue bars (left axis, upper panel) are sums of the normalised fire frequency for all grid cells registering a fire in a given month. ONI data from NOAA (2014a).

Figure 3 –Frequency distributions of the mean and maximum fire frequency per grid cell, El Niño periods of 1982-2010.



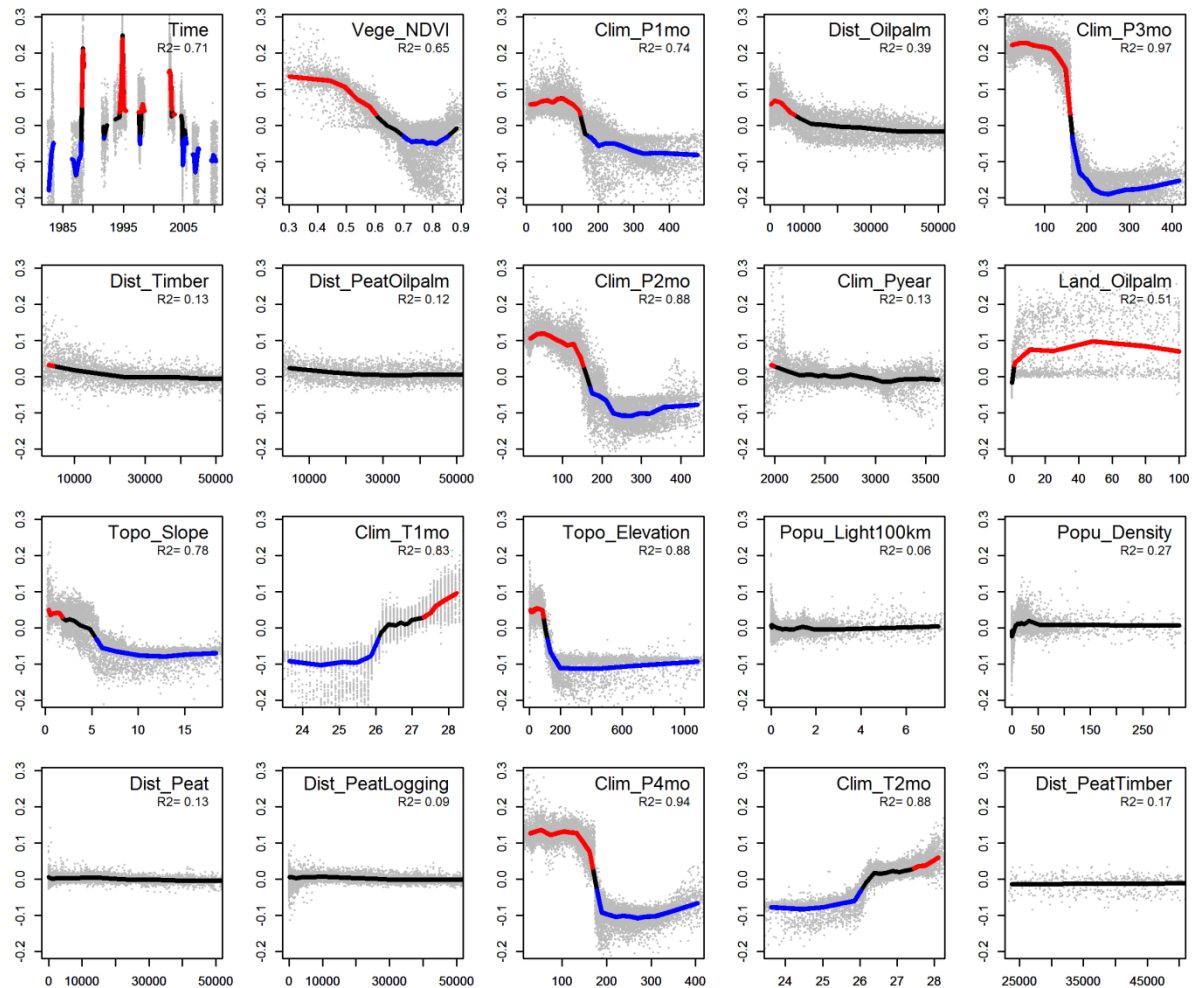
Note: Y-axis is logarithmic. Fire frequencies are normalised. Mean and maximum monthly fire frequencies were calculated over 141 observation months spanning 1982-2010 per grid cell affected by at least one fire during this period. See **Figure 1** for an example of means per grid cell. Multiplying a normalised fire frequency by 26 (the average number of AVHRR GAC images processed per month, **Figure S3**) provides an approximate value of the corresponding nominal or ‘raw’ fire frequency.

Figure 4 – Variable importance for model of monthly fire frequency, El Niño periods of 1982-2010.



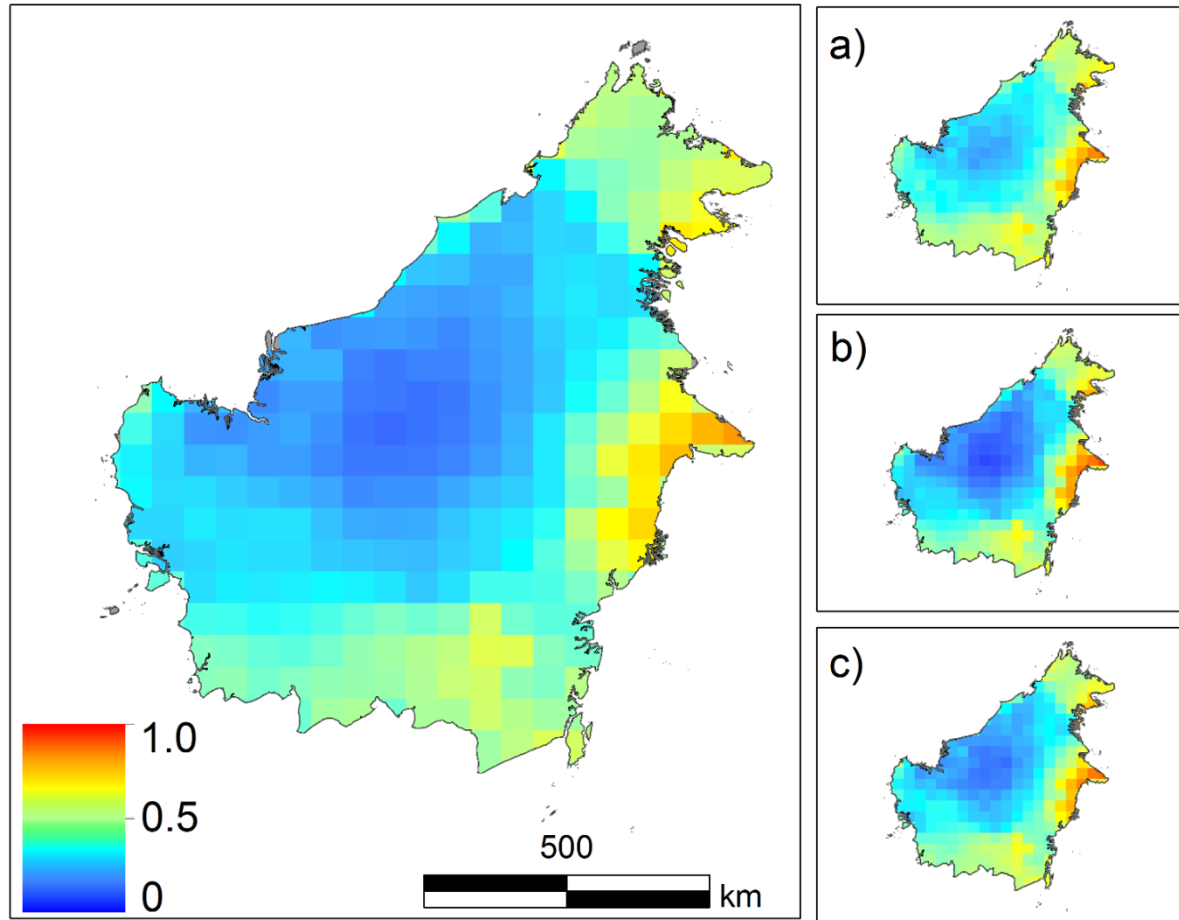
Notes: Variable importance is calculated as the percentage of change in model mean square error upon randomly permuting a predictor's values. Dark bars represent the median variable importance score, boxes the lower and upper quartile scores, and whiskers the minimum and maximum scores based on 100 random-forest models with 100 samples each.

Figure 5 – Relationships between monthly fire frequency and 20 most important predictors.



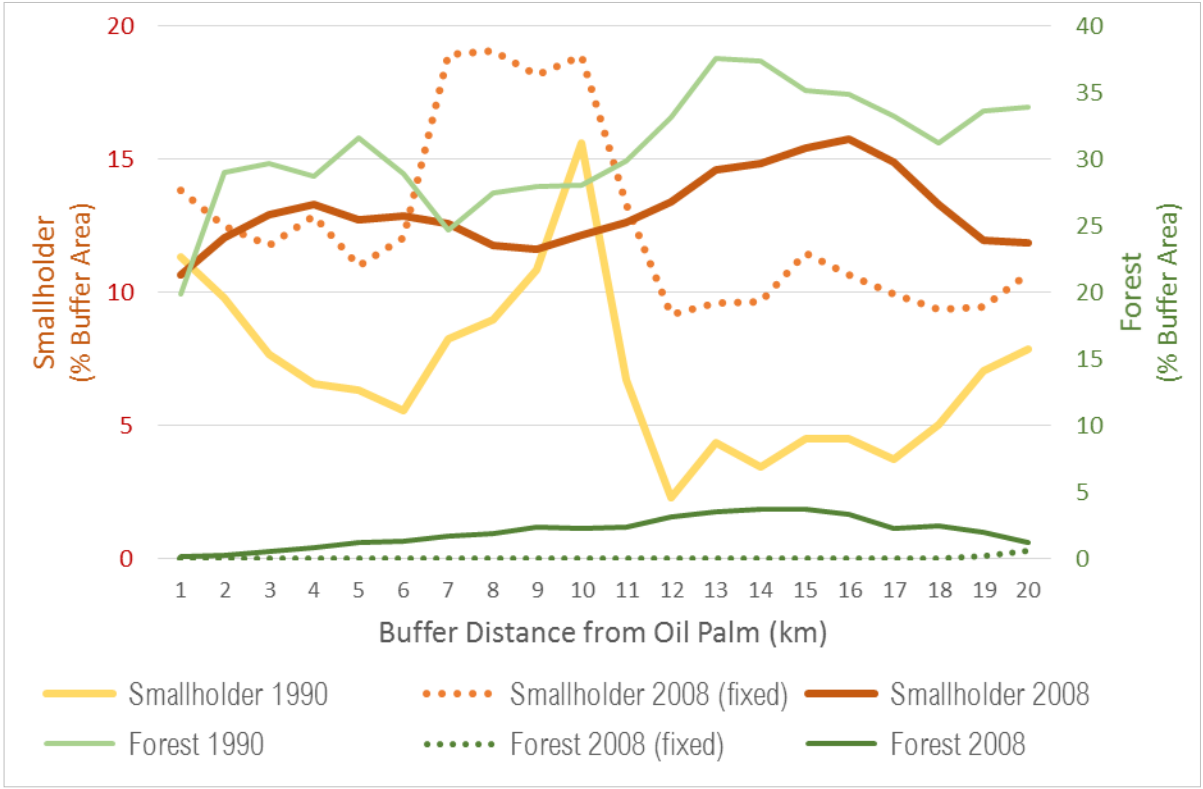
Note: Plots are feature-contribution (FC) plots. Predictors are ordered in terms of their importance to the random-forest model, from left to right and then top to bottom. The y-axis shows a predictor's cross-validated FC, i.e. the expected average change in predicted log-transformed normalised fire frequency at a given value of a predictor. The x-axis shows a predictor's values in units specified in **Table 1**, save for 'Time, which is displayed here as calendar years rather than as months elapsed. Red and blue segments of curve highlight predictor values with meaningful upward and downward feature contributions, respectively. Grey dots show the actual FCs for all observations used to fit the model and the fitted line is a moving average of the modelled FC. R² values pertain to correlations between observed and fitted FCs. Blue and red colours facilitate interpretation by highlighting segments of curves with low and high FCs, respectively. For distance variables (e.g. Dist_Oilpalm), values beyond 50 km are not shown because FC curves were generally flat beyond 50 km.

Figure 6 – Disposition towards higher frequency fires due to short-term critically low precipitation (main panel) defined by the weighted mean proportion of observations of <200 mm precipitation over (a) monthly, (b) three-monthly and (c) two-monthly periods.



Note: In panels *a*, *b* and *c*, a value of 1.0 (0) indicates average precipitation of <200 mm observed with 100% (0%) frequency over the 141 months of interest. The main panel is the weighted average of values of panels *a*, *b* and *c*, where weights for panel *b* (Clim_P3mo) and panel *c* (Clim_P2mo) reflect variable-importance scores scaled relative to the score for panel *a* (Clim_P1mo).

Figure 7 –Percentage smallholder and pristine forest area on peatlands in 1990 and 2008 at increasing distances from oil palm established as of 1990 and 2010, respectively.

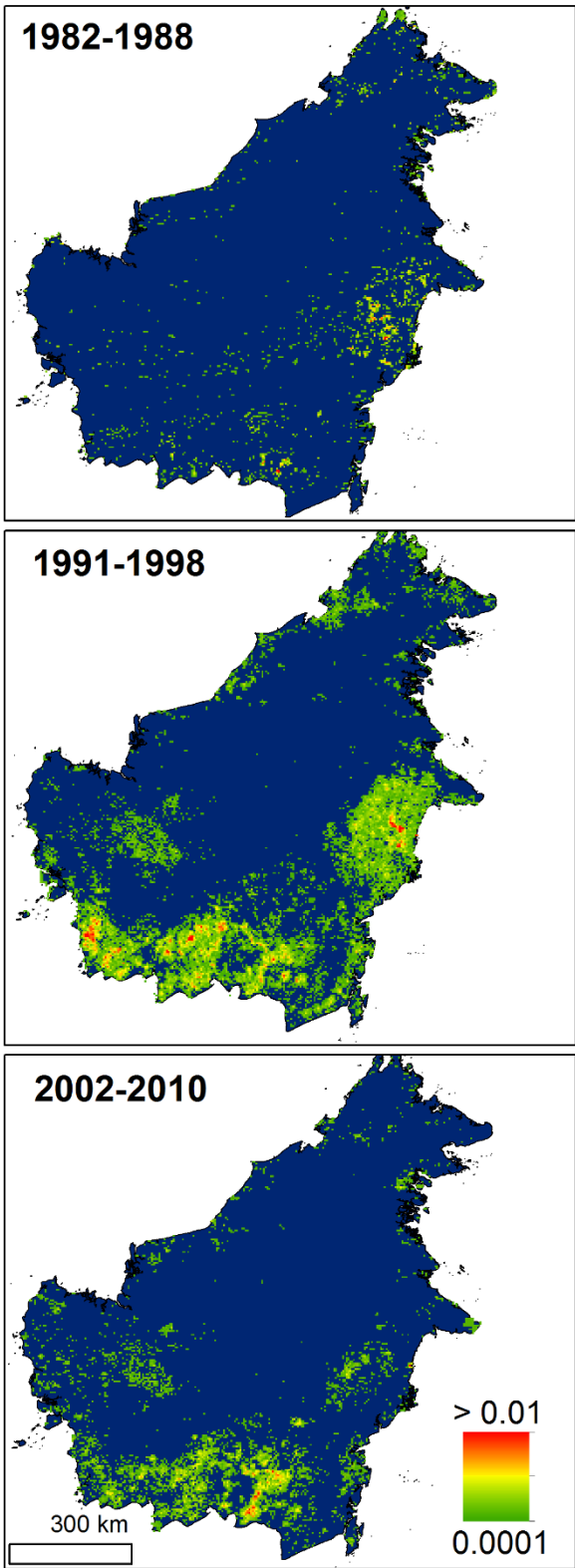


Note: Dotted curves for smallholder and forest areas in 2008 pertain to oil palm in 2010 within a regional extent ‘fixed’ to that of oil palm on or very near peatlands in 1990. Solid curves for 2008 pertain to the larger Borneo-wide extent of oil palm on peatlands as of 2010.

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Figure 8 –Changing epicentres of El Niño fire frequency per decade.



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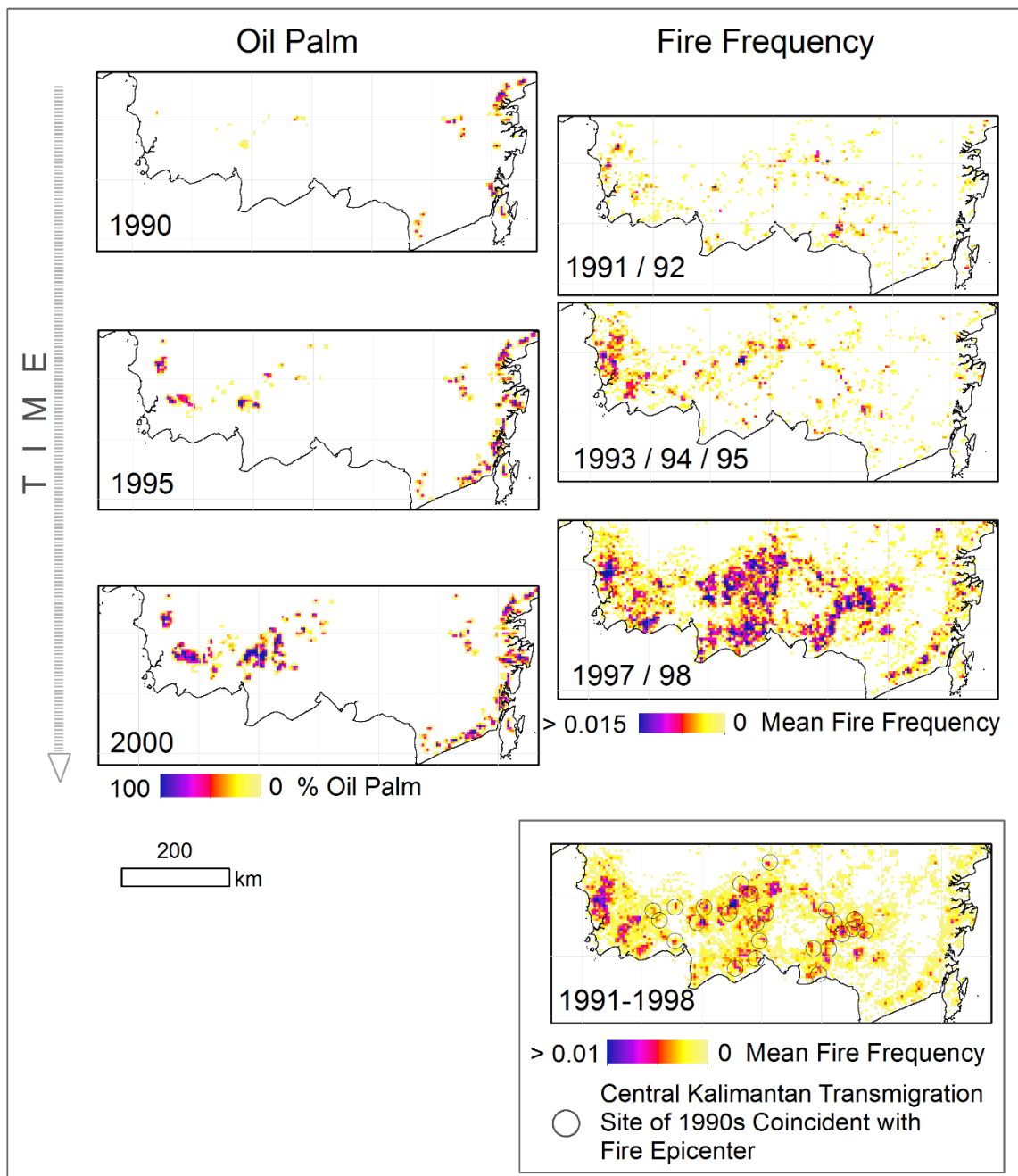
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Note: Shown is normalised monthly fire frequency averaged over all monthly observations per decade.
Maximum average fire frequency and number of months per period: 1982-1988, 0.017 frequency, 38 months;
1991-1998, 0.018 frequency, 51 months; 2002-2010, 0.013 frequency, 52 months.

Figure 9 – Spatial patterns of El Niño fire frequency and oil-palm development in southern Kalimantan over the 1990s.



Tables

Table 1 –Predictors of monthly fire frequency.

Variable	Short name	Units and Notes	Temporal Resolution	Spatial Resolution
<i>Climate</i>				
Mean precipitation (P) over n months ($n=1-4$), e.g., Clim_P4mo is mean precipitation over four months	Clim_P1mo, Clim_P2mo, Clim_P3mo, Clim_P4mo	mm	Monthly	50-km
Mean temperature (T) over n months ($n=1-4$), e.g., Clim_T4mo is mean temperature over four months.	Clim_T1mo, Clim_T2mo, Clim_T3mo, Clim_T4mo	0.1 °C	Monthly	50-km
Average precipitation	Clim_Pann	Mean mm year ⁻¹ over 30 years (1961-1990)	Monthly	50-km
Average temperature	Clim_Tann	Mean °C over 30 years (1961-1990)	Monthly	50-km
<i>Land Cover and Land-Cover Change</i>				
Peatland	Land_Peat	Percent grid cell area	Constant over time	Undefined (vector data)
Oil-palm plantation	Land_Oilpalm	Percent grid cell area	5-10 years, extrapolated to monthly	30-80 m
Timber plantation	Land_Timber	Percent grid cell area	5-10 years, extrapolated to monthly	30-80 m
Logging intensity	Land_Logging	Km logging road per km ² grid cell area	5-10 years, extrapolated to monthly	30-80 m
Degraded peatland due to oil palm, timber, or logging	Land_DrainedPeat	Percent grid cell area	5-10 years, extrapolated to monthly	30-80 m
Degraded peatland due to oil palm	Land_PeatOilpalm	Percent grid cell area	5-10 years, extrapolated to monthly	30-80 m
Degraded peatland due to timber plantation	Land_PeatTimber	Percent grid cell area	5-10 years, extrapolated to monthly	30-80 m
Degraded peatland due to logging	Land_PeatLogging	Percent grid cell area	5-10 years, extrapolated to monthly	30-80 m
<i>Distances from Disturbances</i>				
Distance from oil-palm plantation	Dist_Oilpalm	Meters	5-10 years, extrapolated to monthly	100-m intervals
Distance from timber plantation	Dist_Timber	Meters	5-10 years, extrapolated to monthly	100-m intervals
Distance from logging roads	Dist_Logging	Meters	5-10 years, extrapolated to monthly	100-m intervals
Distance from peatland	Dist_Peat	Meters	Constant over time	100-m intervals
Distance from degraded peatland due to oil palm	Dist_PeatOilpalm	Meters	5-10 years, extrapolated to monthly	100-m intervals
Distance from degraded peatland due to timber plantation	Dist_PeatTimber	Meters	5-10 years, extrapolated to monthly	100-m intervals

Distance from degraded peatland due to logging	Dist_PeatLogging	Meters	5-10 years, extrapolated to monthly	100-m intervals
<i>Vegetation Integrity</i>				
Enhanced Vegetation Index (EVI)	Vege_EVI	EVI value	Monthly	5.5 km
Normalised Difference Vegetation Index (NDVI)	Vege_NDVI	NDVI value	Monthly	8 km
<i>Human Settlement and Time</i>				
Time	Time	Number of months elapsed since June 1982	Monthly	Constant over space
Population density	Popu_Density	Mean population per km ²	10 years, extrapolated to monthly	1 km
Electric nightlight brightness, n-km (n=15, 30, 50 or 100)	Popu_Light15km, Popu_Light30km, Popu_Light50km, Popu_Light100km	Mean brightness within n km of all pixels with a grid cell. Non-denominational units.	Constant over time (max. value over 1996-2010)	1 km, averaged over n-km radius
Distance from inter-urban roads	Dist_Road	Meters	Constant over time (ca. 2000)	100-m intervals
<i>Topography</i>				
Elevation	Topo_Elevation	Meters above sea level	Constant over time	90 m
Slope	Topo_Slope	Degrees	Constant over time	90 m
Aspect	Topo_Aspect	Degrees clockwise from north	Constant over time	90 m
<i>Administrative Units</i>				
Region	Admi_Region	Categorical measure (Brunei, Kalimantan West, Kalimantan South, Kalimantan East, Kalimantan Central, Sabah, Sarawak)	Constant over time	n/a
Country	Admi_Country	Categorical measure (Indonesia, Malaysia and Brunei)	Constant over time	n/a

Table 2 – Summary statistics for fire frequencies, El Niño periods of 1982-2010.

Statistics ^b	Normalised Fire Frequencies ^a		Nominal Fire Frequencies ^a	
	<i>Mean Series</i>	<i>Maximum Series</i>	<i>Mean Series</i>	<i>Maximum Series</i>
Average	0.0007	0.058	0.022	1.68
Median	0.0005	0.048	0.014	1
90 th percentile	0.0016	0.105	0.050	3
Maximum	0.0071	0.429	0.184	11

Notes: (a) Series of mean and maximum fire frequencies are calculated per individual grid cell affected by at least one fire over the 141 months of observation spanning 1982-2010. Statistics for the ‘mean series’ and ‘maximum series’ refer respectively to the mean and the maximum monthly fire frequency observed for a given cell. See **Figure 1** for an example of the mean series for normalised fire frequencies. (b) Statistics are calculated ‘globally’ across all fire-affected grid cells the mean or maximum series. For example, for normalised monthly fire frequencies, the maximum of the mean fire frequencies observed for each fire-affected grid cells over the 141 months is 0.0071. Similarly, the maximum of the maximum fire frequencies observed for each per fire-affected grid cell over the 141 months is 0.429.

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Supplementary Materials

Fire Activity in Borneo Driven by Industrial Land Conversion and Drought During El Niño Periods, 1982-2010

Global Environmental Change

Contents

Text S1 – Fire Detections using AVHRR GAC Data.

Text S2 – Random Forest Modeling of Fire Frequency

Figure S1 – Comparison of monthly fire activity in Borneo as measured by MODIS fire radiative power and by normalised AVHRR GAC fire frequencies, aggregated monthly for all MODIS and AVHRR GAC active-fire detections respectively, 2002-2010. AVHRR GAC fire frequencies are observed for El Niño periods only.

Figure S2 – Aggregate fire frequency according MODIS and AVHRR GAC data during El Niño periods, 2002-2010: (a) MODIS fire events, (b) normalised GAC fire frequency.

Figure S3 – Number of daily AVHRR GAC scenes processed and analysed as active-fire maps by month during the El Niño periods of 1982-2010.

Figure S4 – Total nominal fire frequency across El Niño periods of 1982-2010.

Figure S5 – Oil-palm coverage and proximity to oil palm per grid cell.

Figure S6 – Logging roads and disposition to higher frequency fires due to short-term critically low precipitation levels, by logging period.

Figure S7 – Interactive effects on El Niño fire frequency of monthly precipitation (Clim_P1mo , mm month^{-1}) vs. (a) logging intensity (Land_Logging , km roads per km^2) and (b) NDVI (Vege_NDVI), a proxy for landscape perturbation.

Figure S8 – Difference in mean monthly February-April precipitation for El Niño periods of 2000s compared to El Niño periods of 1980s and 1990s

Figure S9 – The degree to which landscapes surrounding oil palm and timber plantations overlap each other at varying distances from plantations, 2010.

Text S1 – Fire Detections using AVHRR GAC Data

Thermal radiation emitted by landscape fires is particularly intense in the midwave-infrared (MWIR) spectral region (Robinson, 1991; Wooster et al., 2013). AVHRR data records both MWIR and ‘ambient’ longwave infrared (LWIR) signals at each pixel, and thus a pixel containing an active fire significantly elevates the MWIR signal relative to the coincident ‘ambient’ LWIR signal (Matson and Dozier, 1981; Robinson, 1991), even if the fire is highly sub-pixel in area or is smoldering and/or partly hidden from view (cf. Siegert et al., 2004; Elvidge et al., 2015)). This fact enables AVHRR pixels containing actively flaming, smoldering, or even sub-surface actively burning fires to be discriminated from those that do not contain such heat sources using relatively simple threshold-based algorithms referencing MWIR-LWIR brightness temperature differences (Robinson, 1991; Wooster and Strub, 2002). Such algorithms can detect active fires even when fires span an area covering only 1/1000 to perhaps 1/10,000 of the pixel area, depending on the fires’ thermal characteristics (Robinson, 1991). Cloud cover obscures fires from view in MWIR and LWIR wavelengths, but cloud is far less prevalent across Borneo during dry periods coincident with El Niño events, particularly in the more fire affected lowlands (Wooster et al., 2012). Smoke generally does not obscure fires at these wavelengths (Wooster et al., 2013). Therefore, by applying a threshold-based active fire detection algorithm to AVHRR imagery collected at a daily or higher temporal resolution in a similar way to Wooster et al. (2012), we were able regularly map active fires and thus derive monthly fire frequency maps for Borneo.

AVHRR data is nominally collected with each individual pixel having a ground area of 1.1 km × 1.1 km at nadir, but this ‘Local Area Coverage’ (LAC) imagery was not routinely archived by NOAA due to data storage restrictions on-board the POES satellites that carry the AVHRR instrument. Therefore, for most periods and regions, including Southeast Asia, historical AVHRR data mostly consist of the spatially sub-sampled ‘Global Area Coverage’ (GAC) version of the original LAC imagery, which were able to be stored on-board and are available daily since the late 1970’s (Wooster et al., 1998; Wooster and Strub, 2002; Wooster et al., 2012). Full details of the GAC sub-sampling procedure are provided by Robel (2009). Effectively each GAC pixel is the average of three of four along-scan constituent LAC pixels and every third scan line, for which reason the original GAC pixel dimensions are reported as 1.1 km × 4.4 km. Thus the assumption is made that our resampled 0.04° square GAC pixels are a statistical sample representative of coincident but unobserved LAC pixels.

Satellite active fire detections derived from AVHRR GAC data are the only source of daily active fire information across Borneo prior to the advent of the MODIS era in 2000. The availability of ~1 km spatial resolution MODIS data was preceded by that from the ATSR sensors in the mid-1990s (most notably ATSR-2), but these did not cover Borneo in a single scene due to a narrow field of view and had a ~3-day revisit rate for most of its mission lifetime. The consistent, regular and very long-term coverage is the primary advantage of GAC active-fire data. By encompassing all El Niño periods including and beyond the extreme El Niño of 1982/83 – the first major modern El Niño and fire event in Borneo shortly after the onset of industrial agriculture and forestry activities – our GAC active-fire dataset spans the full diversity of historical El Niños in terms of climatic dynamics and levels of landscape perturbation. Accounting for this diversity of El Niño events and levels of landscape perturbation is critical for robust, generalisable inferences regarding the drivers and patterns of fire activity, considering that climatic conditions and levels of landscape change have varied greatly since the early 1980s. Our temporally comprehensive analysis of Borneo’s fire activity realized using GAC data complements the far more common analyses of fire activity associated with solitary El Niño events, which often also focus on either the most extreme examples (Siegert and Hoffmann, 2000; Siegert et

al., 2001) or on periods of the 2000s coincident with the later stages of Borneo's long agro-industrial transformation (Langner et al., 2007; Miettinen et al., 2010).

Prior work has demonstrated the reliability of AVHRR GAC active fire detections for the study of fire events in Borneo during El Niño events (Wooster et al., 1998; Wooster and Strub, 2002; Wooster et al., 2012). Comparisons of aggregate, Borneo-wide monthly fire counts derived from the sub-sampled GAC data and the corresponding original AVHRR LAC having 1.1 km spatial resolution show differences of only 3 to 13% once GAC-derived fire counts were scaled to account for spatial sub-sampling (Wooster and Strub, 2002). These comparisons also found that when a GAC pixel was flagged as containing an active fire, all the constituent LAC pixels comprising the GAC pixel were usually themselves also flagged (Wooster and Strub, 2002). Wooster et al. (2012: Fig.6) similarly showed that aggregate, Borneo-wide monthly active-fire counts derived from GAC data are very highly correlated with fire counts derived from the 1 km ATSR satellite Word Fire Atlas (Page et al., 2008), which has itself been shown to capture fire activity well across Borneo (Fuller and Murphy 2006).

Further analysis conducted for the present analysis shows a pronounced correspondence between our normalized AVHRR GAC monthly fire frequencies and MODIS' active fire radiative power (FRP) data aggregated monthly across Borneo between 2002 and 2010 (**Figure S1**). The FRP of an active fire pixel describes the rate of electromagnetic energy released by the fires located within it, and is very highly correlated with rates of biomass consumption by fire (Wooster et al., 2005). The correspondence seen in **Figure S1** between the periodic extreme highs of FRP and our AVHRR GAC estimates of fire frequency during El Niño periods support observations by Van der Werf et al. (2010) that the vast majority of biomass burning in Borneo is concentrated within El Niño episodes. Accordingly, our GAC-derived estimates of fire activity for 141 months of El Niño episodes between June 1982 and June 2010 are believed to capture the vast majority of fire activity and biomass burning that occurred over the entire 1982-2010 period.

The strong temporal correspondence between GAC and other active-fire datasets noted above does not necessarily mean similar correspondence exists in terms of the spatial patterns of fire activity. Indeed, detailed spatial comparisons of active-fire events derived from AVHRR GAC, MODIS and ATSR data have not yet been published. In general, comparisons of satellite active-fire detections derived from different moderate-to-coarse spatial resolution sensors have highlighted their sometimes limited spatial agreement (Liew et al., 2003; Stolle et al., 2004; Schroeder et al., 2008). This reflects not only their differences in spatial resolution, but also for example differences in overpass timing and imaging frequency, sensitivity of the active fire-detection algorithms used, the spectral bands of observation and corresponding levels of atmospheric opacity, and so on, with different sensors effectively sampling different but partially overlapping aspects of the much larger universe of total fire activity. Some insight may however be gleaned from Schroeder et al.'s (2008) comparison of Brazilian active-fire detections according to MODIS active-fire detection data (Giglio et al., 2003) and the NOAA Geostationary Operational Environmental Satellite (GOES) Wildfire Automated Biomass Burning Algorithm (WFABBA, <http://wfabba.ssec.wisc.edu/>), the latter of which has a spatial resolution similar to that of our AVHRR GAC-derived active-fire data. Findings that may hold some relation to our GAC data include (i) active fire events had to be 2-4 times greater in size for GOES-WFABBA than for MODIS if they were to achieve a >50% true detection probability, depending on the density of forest coverage (a proxy for fuel consumption and fire intensity); (ii) rates of active fire detection omission were greater for GOES-WFABBA because it tended to overlook smaller, dispersed and lower-intensity fires associated with small-scale agricultural maintenance (e.g., pasture burning) and savannah fires;

and (iii) commission error rates were comparable for MODIS and GOES-WFABBA, regardless of forest coverage density.

In **Figure S2** we show a strong first-order spatial agreement between our GAC-derived active-fire data and MODIS active-fire data collected over 2000-2010. Shown specifically are the total normalized monthly fire frequencies derived from our AVHRR GAC data, and the total number of MODIS 'MCD14ML' fire events per GAC pixel during the 52 months of observation spanning 2002-2010. Regional epicenters of high-frequency fire activity highlighted by the MODIS data (Areas 1-5 in **Figure S2**) are comparatively well captured by the GAC data with respect to their spatial distribution and variations in fire frequency, even though the GAC data entail a significantly higher minimum fire size detection threshold compared to MODIS and represent only nighttime detections as opposed to MODIS' daytime and nighttime detections. The locations of these fire epicenters suggest that they correspond primarily to industrial agricultural and forestry operations, aligned transmigration, forest conversion, and 'wildfires', including on peatlands, all of which entail relatively large fire events. As expected, our GAC data captured disperse, low frequency, and apparently small-scale agricultural fire activity in relatively cleared regions like West Kalimantan less extensively than the finer-scale MODIS data (Areas 6-8 in **Figure S2**). Dispersed low-level fire activity in Areas 9 and 10 of **Figure S2** were also captured less well by the GAC data for unknown reasons presumably related to the relatively inability of GAC data to capture small-scale agricultural fires. Miettinen and Liew (2009: Fig.3) illustrate the diminutive scale of fire activity associated with smallholder agriculture compared to industrial forest conversion and forest degradation with reference to post-fire burn "scars". Overall, the number of MODIS fire events observed per GAC pixel during the 52 months of the 2000s significantly predicted the total normalized GAC fire frequency for the same period (OLS regression, $p < 0.001$, $r = 0.56$ for analysis of GAC pixels with > 0 normalized fire count; $p < 0.001$, $r = 0.51$ for analysis of GAC pixels with > 0 MODIS fire event).

These analyses indicate that our monthly fire frequencies estimated for the El Niño periods of 1982-2010 using AVHRR GAC data are likely to have reliably captured the vast majority of major fire events over this period and, by extension, the majority of all major fire events that occurred over the entire duration of the study. The great advantage of using the GAC data to this end is that the study duration can be greatly extended to years far earlier than those of the MODIS era, i.e., back to El Niños that occurred during the 1980s and 1990s. The type of broad-scale fire events detectable with GAC data are likely associated primarily with incremental forest change and conversion, as well as 'wildfires' that likely resulted from both planned and accidental ignitions. Dispersed and low-level fire activity, particularly that associated with the maintenance of smallholder agricultural plots in relatively cleared landscapes, is likely under-estimated by GAC data, and this supposition is supported by evidence provided by our comparison with higher spatial resolution MODIS active fire detections.

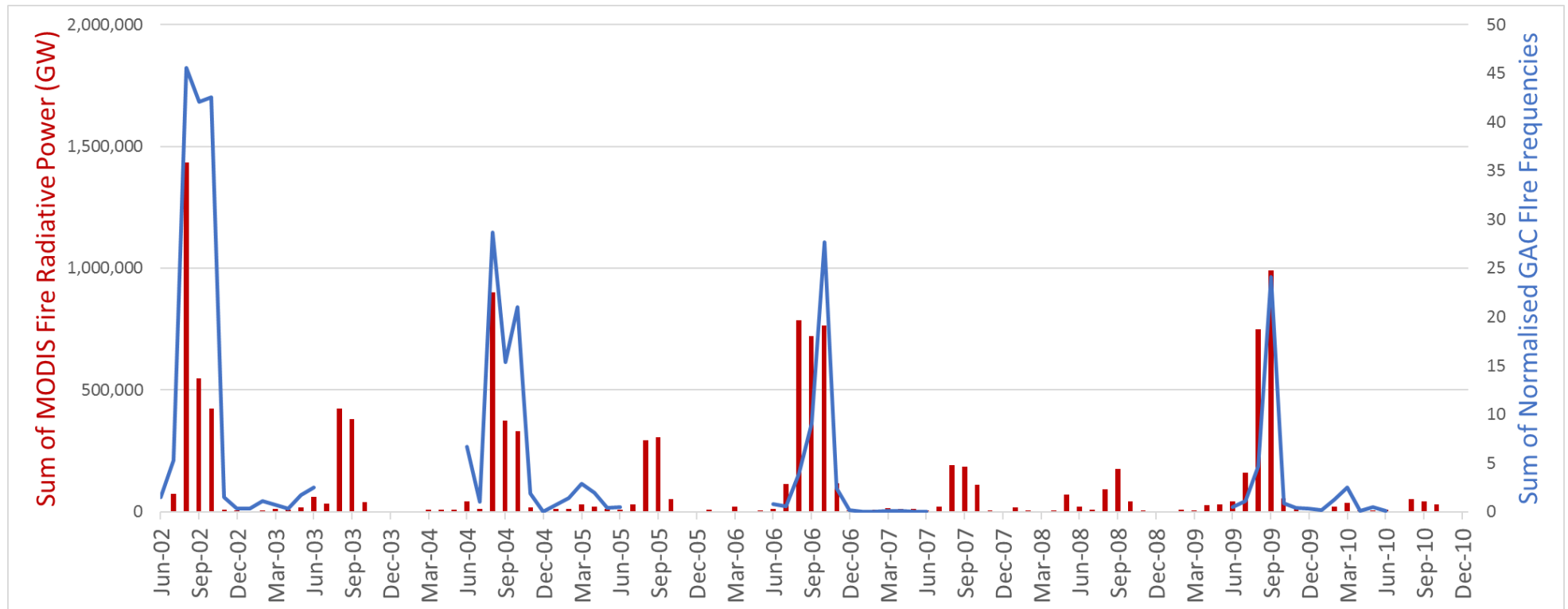
Text S2 – Random Forest Modeling of Fire Frequency

Our random-forest model drew 1000 bootstrapped samples from the 10,716 voxels and, for each bootstrapped sample, developed a regression tree predicting the log-transformed normalised monthly fire frequency per voxel using a random subset of 13 predictors in **Table 1**. Measures of variable importance and model error were determined for each regression tree using ‘out-of-bag’ observations not included in a sample, and these measures were averaged over all regression trees.

For measures of variable importance specifically, the randomly permuted values of predictors were for the ‘out-of-bag’ voxels of a given bootstrap sample. Like the original values of out-of-bag voxels of a bootstrap sample, permuted values are passed through the corresponding regression tree. The difference between the mean square errors for the tree with original and permuted values is averaged over all trees in the random forest and standardized by the standard deviation of the differences in order to define the variable importance score (Liaw and Wiener, 2002).

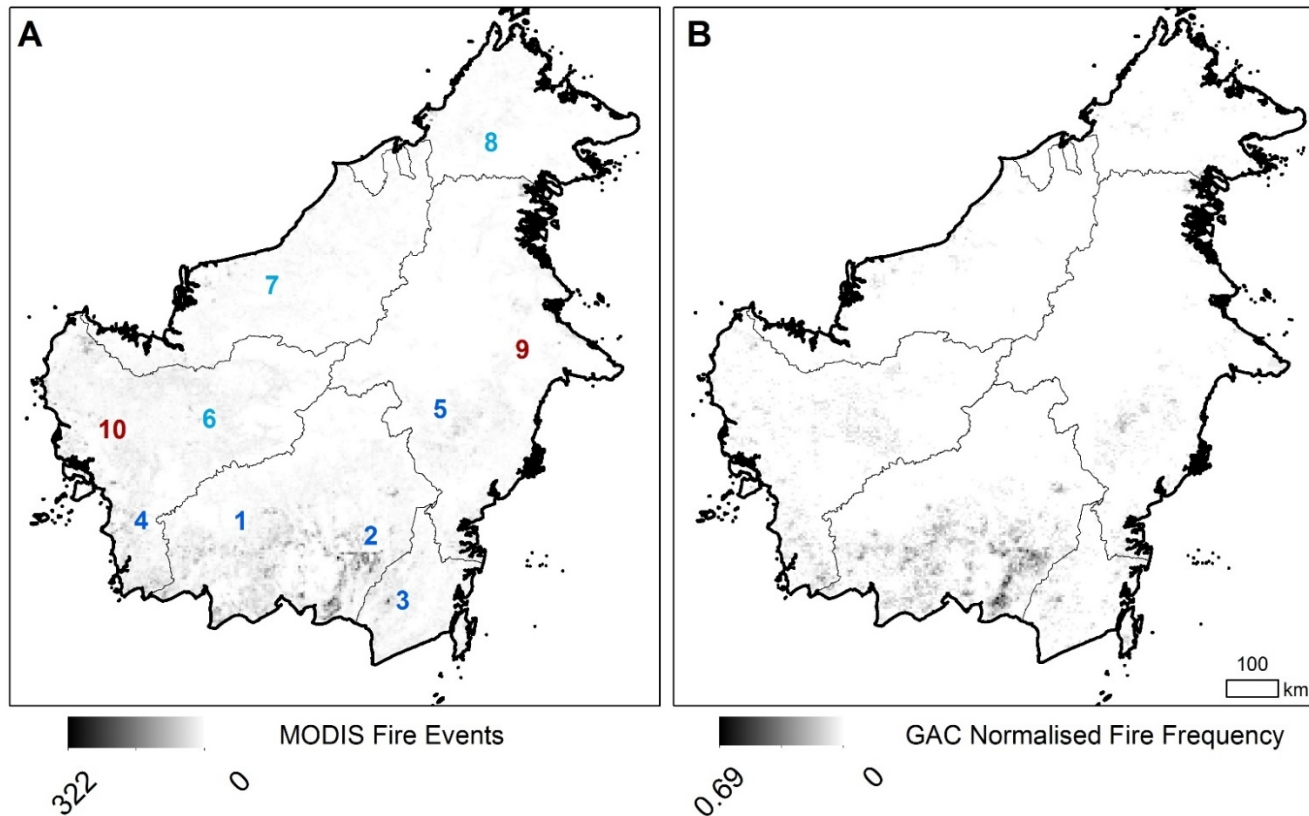
A random-forest model has several advantages for the characterization of complex fire patterns. The actual effects of each individual predictor may be determined without bias despite multi-collinearity, ensuring that many potentially relevant predictors can be explored without overlooking important predictors or limiting consideration to select predictors believed *a priori* to be ‘most relevant’ (Cutler et al., 2007). Further, inevitably non-linear, interactive, and spatially-variable relationships may be profiled despite extreme values in the data. Also, generalisation error is limited (i.e., model error \approx true error) and overfitting is impossible due to randomization and the large number of trees (Segal, 2004; Prasad et al., 2006). Similarly, measures of variable importance and model error are unbiased and generalisable due to their calculation using out-of-bag observations (Breiman, 2001), eliminating the necessity of cross-validation and in turn allowing model development using all available observations. Further details on the random-forest approach are provided by Breiman (2001), Prasad et al. (2006) and Siroky (2009).

Figure S1 – Comparison of monthly fire activity in Borneo as measured by MODIS fire radiative power and normalised AVHRR GAC fire frequencies, aggregated monthly for all MODIS and AVHRR GAC active-fire detections respectively, 2002-2010. AVHRR GAC fire frequencies are observed for El Niño periods only.



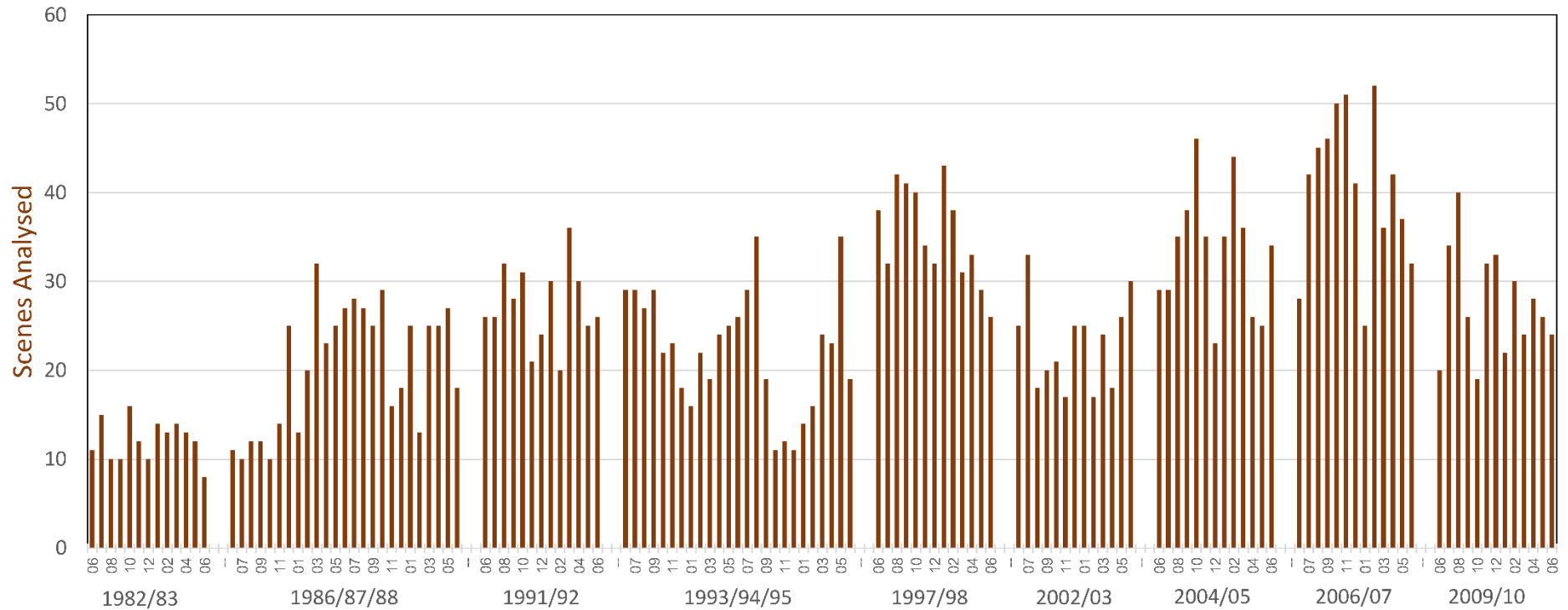
Note: For measures of fire radiative power (MODIS) and normalised monthly fire frequency (AVHRR GAC), the aggregate monthly values graphed above represent the sum of observations for all active fires detected using the respective satellite data during a given month in Borneo. Fire radiative power is defined as per Wooster et al. (2003) and taken from the official MODIS FIRMS active-fire data sourced from EarthData (2017). MODIS data are approximately twice-daily daytime and night-time observations with detection confidence levels of >50%. Normalised monthly GAC fire frequencies are as per **Figure 2**.

Figure S2 – Aggregate fire frequencies according MODIS and AVHRR GAC data during El Niño periods, 2002-2010: (a) MODIS fire events, (b) normalised GAC fire frequency.



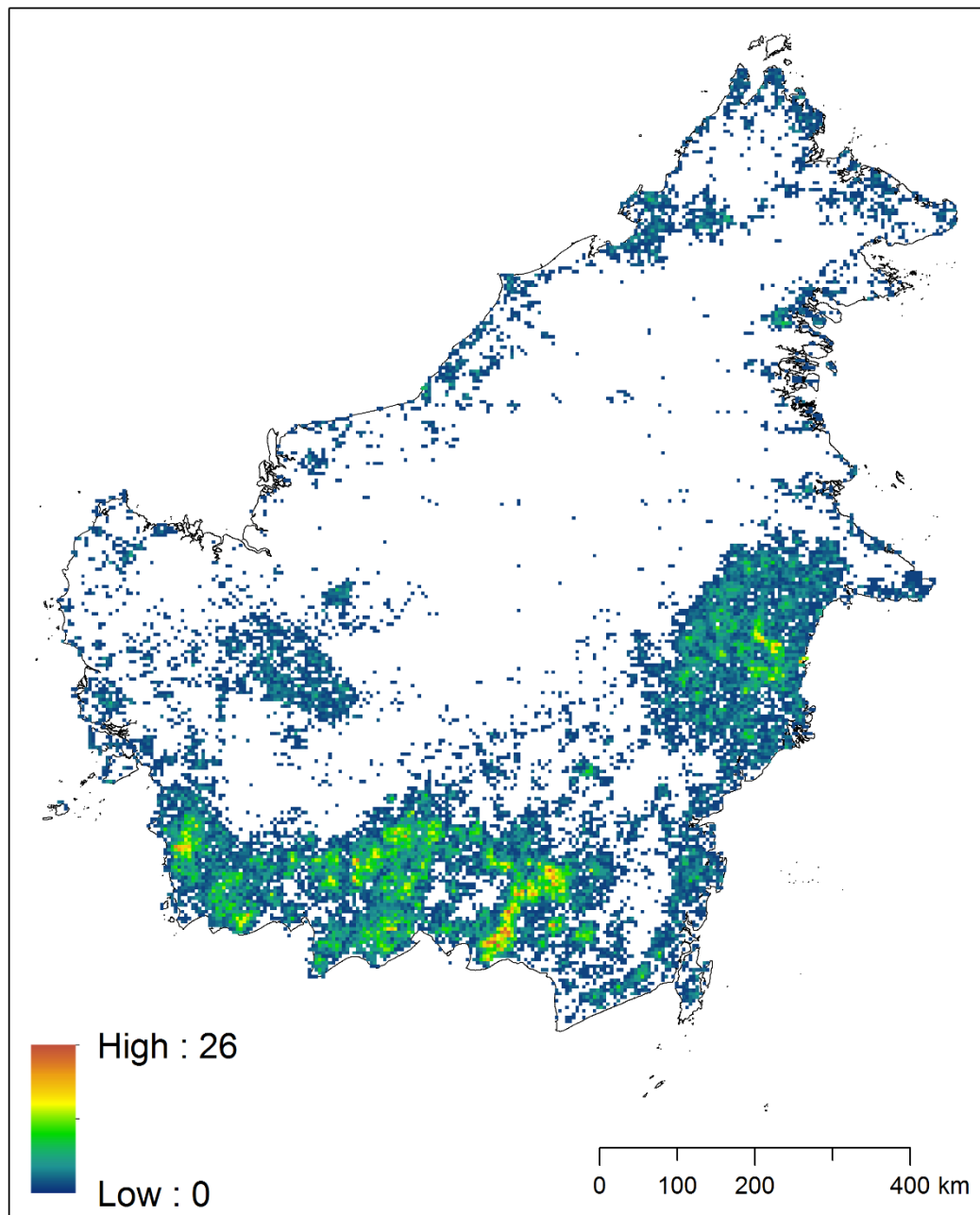
Note: Numbers in Panel A flag areas showing varying levels of spatial agreement with the AVHRR GAC-derived active fire data of Panel B, discussed in Text S1. Areas 1-5: strong agreement in forest conversion and industrial land use regions; Areas 6-8: partial agreement in small-scale agricultural regions; Areas 9-10: poor agreement in small-scale agricultural regions. Observation period spans 52 El Niño months of observation between June 2002 and June 2010 (see **Figure S3**). MODIS FIRMS active-fire detections were sourced from EarthData (2017) and include approximately twice-daily daytime and night-time observations with detection confidence levels of >50%. Normalised monthly AVHRR GAC fire frequencies are derived from night-time data only and were summed for all observation months of the El Niño periods of 2002-2010.

Figure S3 – Number of daily AVHRR GAC scenes processed and analysed as active-fire maps by month during the El Niño periods of 1982-2010.



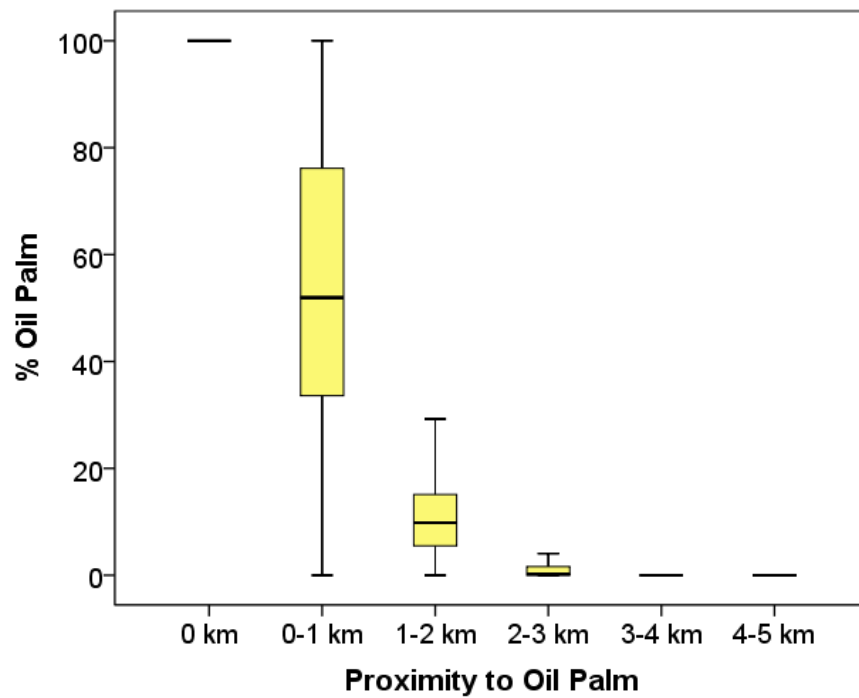
Note: Labels on the x-axis denote to every second month (n=141 months). On average, 25.9 night-time AVHRR GAC scenes were processed per month for use in deriving the monthly active fire frequency maps.

Figure S4 – Total nominal fire frequency across El Niño periods of 1982-2010, as calculated from AVHRR GAC active fire detections.



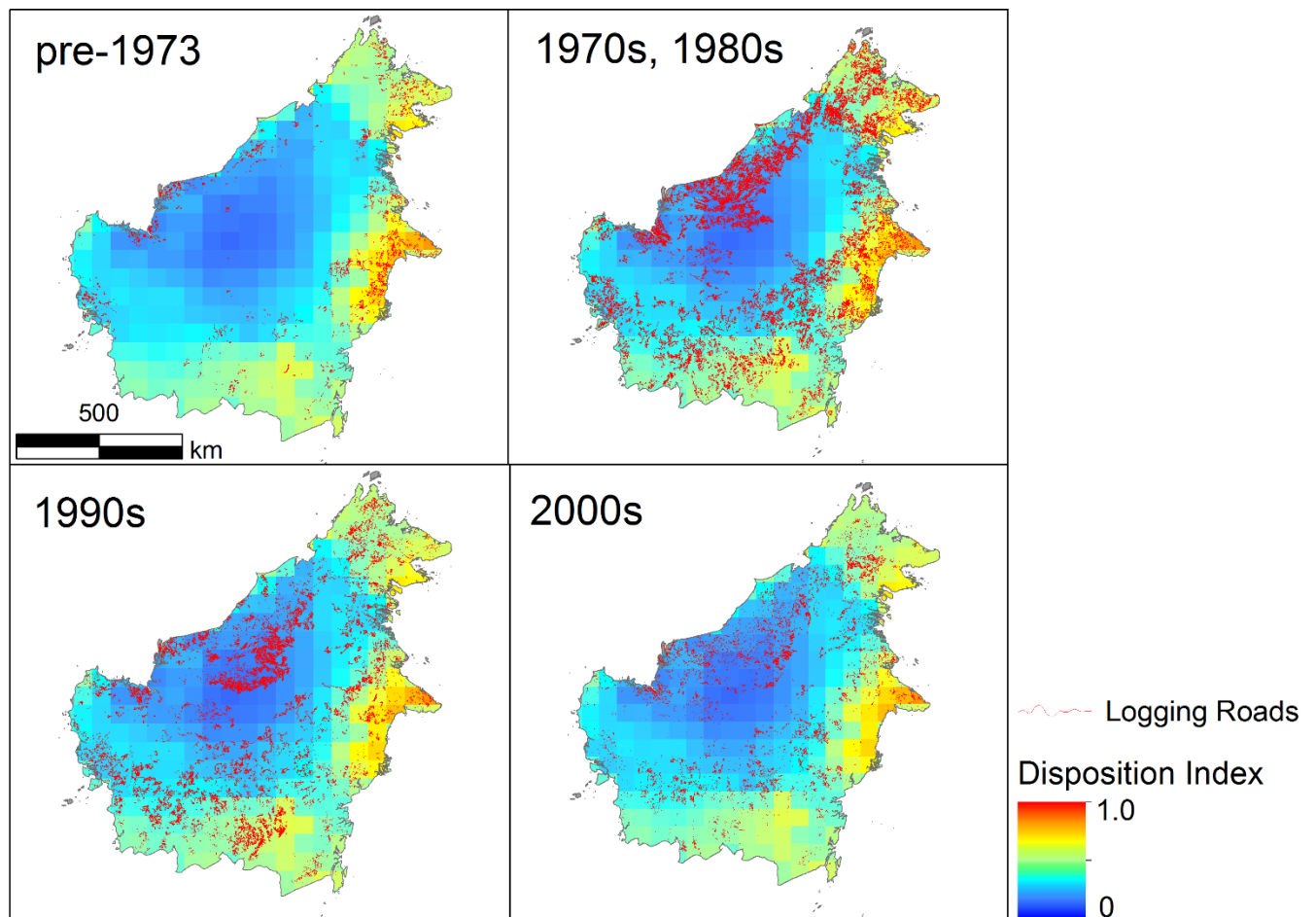
Notes: The total nominal monthly frequency is the sum of nominal monthly frequencies over all 141 months of observation. See **Figure 1** for the mean normalised monthly fire frequency.

Figure S5 – Oil-palm coverage and proximity to oil palm per grid cell.



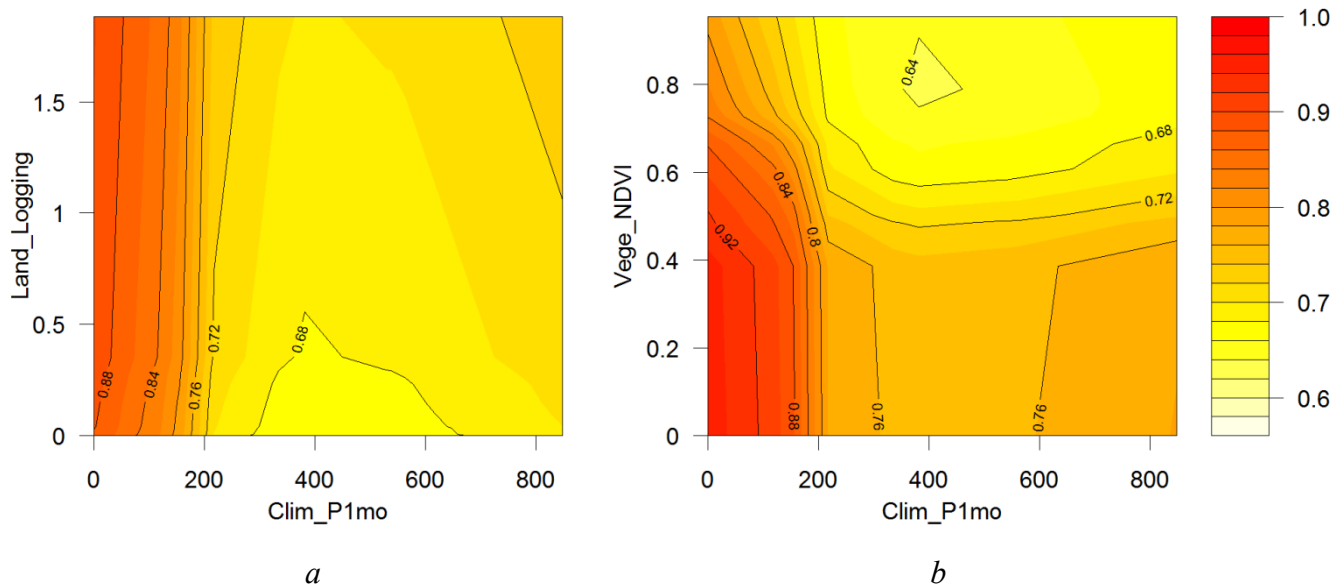
Notes: Percentage oil-palm coverage and oil-palm proximity are calculated per grid cell. Oil-palm proximity is defined as the mean distance from any point in a grid cell to the nearest oil palm patch. A mean proximity of 0 km implies that the entirety of the grid cell is dedicated to oil palm. Number of grid cells per proximity category: 0 km, 649 cells; 0-1 km, 4502 cells; 1-2 km, 2036 cells; 2-3 km, 1524 cells; 3-4 km, 1397 cells; 4-5 km, 1306 cells.

Figure S6 –Logging roads and disposition to higher frequency fires due to short-term critically low precipitation levels, by logging period.



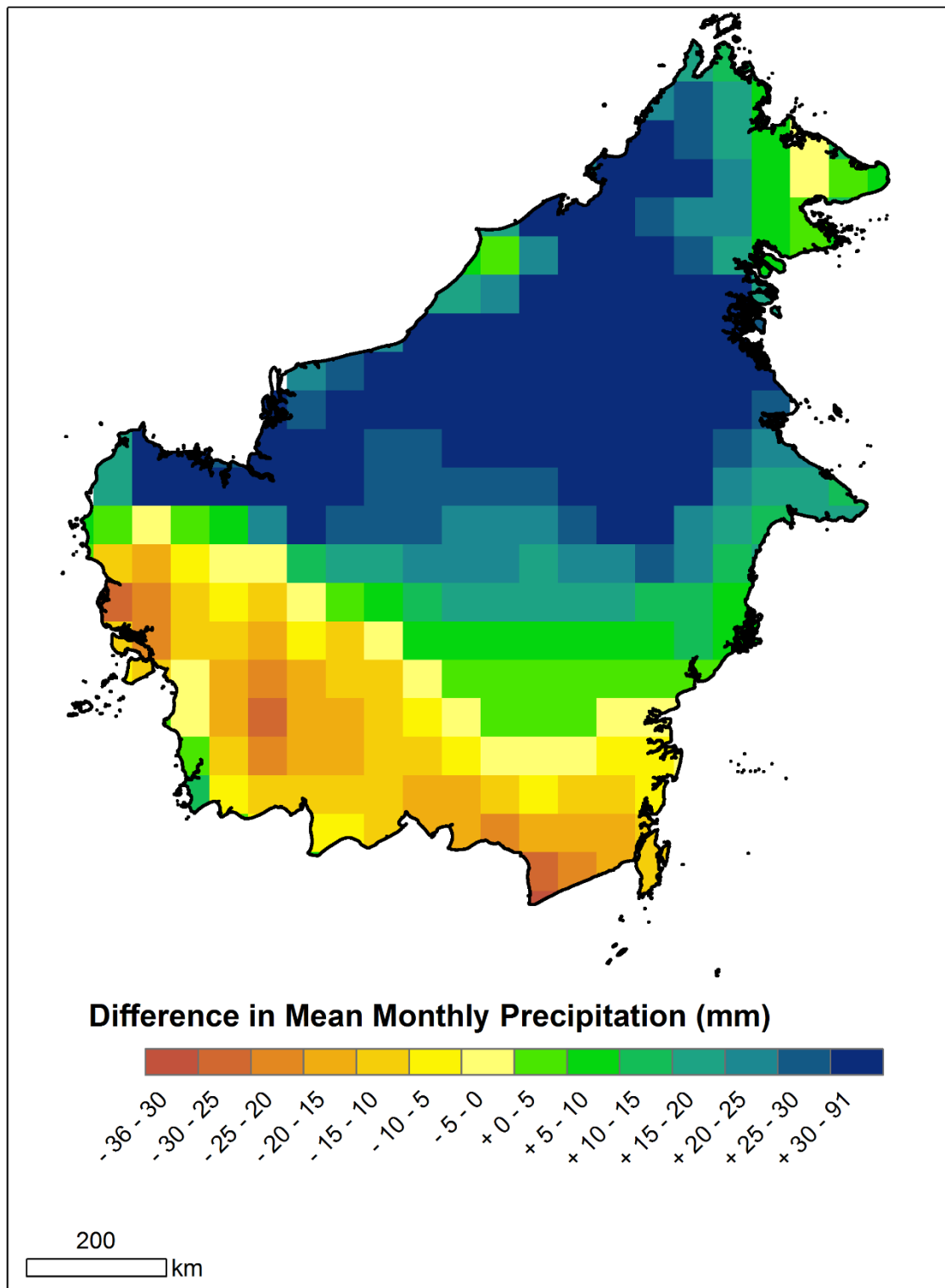
Notes: Index values were defined by the weighted mean proportion of monthly, three-monthly and two-monthly observations with < 200 mm average precipitation during the 141 months of observation, where weights are proportional to importance scores of these precipitation variables (Figure 4).

Figure S7– Interactive effects on fire frequency of monthly precipitation (Clim_P1mo, mm month⁻¹) vs. (a) logging intensity (Land_Logging, km roads per km²) and (b) NDVI (Vege_NDVI), a proxy for landscape perturbation.



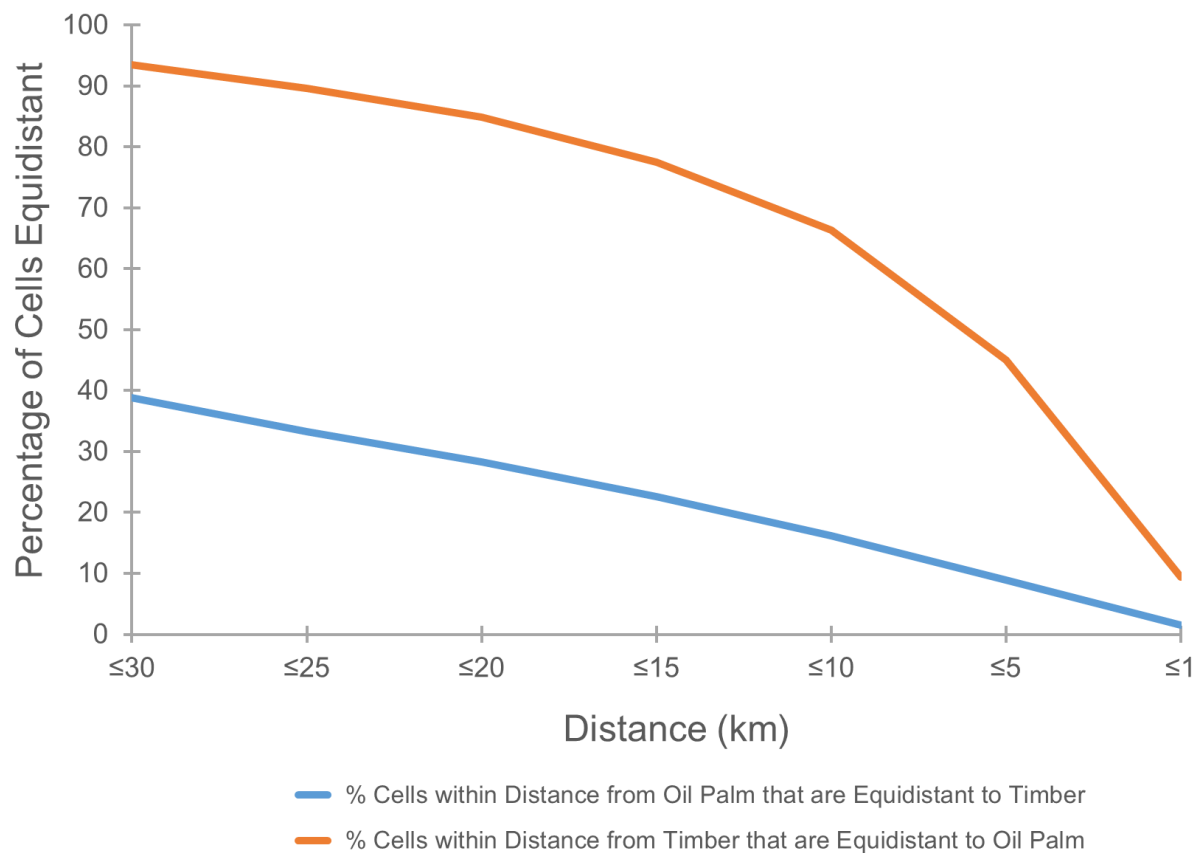
Note: Graphs are tri-variate partial dependence plots showing interactive effects of two predictor variables (x and y axes) on fire frequencies (contours and shading). Contours and shading indicate log transformed normalised monthly fire frequency, i.e., the model response variable. Panel (a): No interaction between monthly precipitation and logging-road density is apparent, as evidenced by the straight vertical contours for all values of logging-road density and monthly precipitation. The graph evidences a strong univariate effect of precipitation on fire frequency, regardless of logging-road density. Panel (b): A strong interaction is observed between monthly precipitation and NDVI (landscape perturbation). The interactive effect occurs where precipitation is < 200 mm month⁻¹ (very dry conditions) and NDVI values suggest intermediate levels of landscape perturbation (NDVI of ~0.5-0.7), as evidenced by the curved contours in this range. This interaction occurs at NDVI values over which the univariate effect of NDVI on fire frequency is relatively low (**Figure 5**).

Figure S8 – Difference in mean monthly February-April precipitation for El Niño periods of 2000s compared to El Niño periods of 1980s and 1990s.



Note: Positive (negative) differences in precipitation indicate an increase (decrease) in mean monthly precipitation during February-April for El Niño observation periods of the 2000s relative to February-April for El Niño observation periods of the 1980s and 1990s, i.e., El Niño observation periods occurring between June 1982 and December 1998.

Figure S9 – The degree to which landscapes surrounding oil palm and timber plantations overlap each other at varying distances from plantations, 2010.



Interpretive Note: The key insight derived from this graph is that the land-change dynamics heightening fire frequencies within the critical distance of 10 km from oil-palm plantations (**Figure 5**) may largely be the same as those occurring nearby timber plantations. The curves graphically depict the proximity of oil-palm plantations to timber plantations and vice versa at decreasing distances from a given plantation type. For example, at ≤ 30 km on the x-axis, the blue oil-palm curve indicates that approximately 40% (y-axis) of all grid cells that are ≤ 30 km from oil-palm plantation are also ≤ 30 km from a timber plantation. Similarly, again at ≤ 30 km on the x-axis, the orange timber-plantation curve indicates that approximately 95% (y-axis) of all grid cells that are ≤ 30 km from a timber plantation are also ≤ 30 km from an oil-palm plantation. Considering that fire frequency around timber plantations increases only when $\sim \leq 5$ km from timber plantations (**Figure 5**), it is noteworthy that 45% of grid cells ≤ 5 km from timber plantations were equally close to oil palm. The converse is not the case, however; only 9% of grid cells ≤ 5 km from oil palm were equally close to timber plantations.

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